```
            INFORMATION ABOUT DATA:

                         -> THE DATA SET CONSISTS OF HAND WRITTEN IMAGES
ALONG WITH THIER CLASS LABELS

                         -> THE MNIST DATASET IS IN BUILT IN TENSOR FLOW
AND ALSO KERAS



             OBJECTIVE:

                          -> USING KERAS ON THE MNIST DATA WHICH USER TEN
SOR FLOW IN THE BACKEND

                          -> TO TRY DIFFERENT ARCHITECTURES OF DIFFERENT
NUMBER OF NEURONS IN EACH LAYER

                          -> TO TRY DIFFERENT ACTIVATION FUNCTIONS

                          -> TO INTRODUCE BATCH NORMALIZATION AND DROP OU
T IN THE NETWORK

                          -> TO ANALYZE THE WEIGHTS OF EACH LAYER

                          -> TO USE DIFFERENT OPTIMIZATION ALGORITHMS

                          -> USING ACCURACY AS THE MEASURE CHECK
```

```
-> Importing the required libraries

-> importing the data set which is in built in keras
```

In [0]:

```
from keras.utils import np_utils
from keras.datasets import mnist
import seaborn as s
from keras.initializers import RandomNormal
import matplotlib.pyplot as mp
import numpy as np
```

In [0]:

```
def dynamic_plot(x, v, t, ax, colors = ['b']):
  ax.plot(x, v, 'b', label = 'Validation loss')
  ax.plot(x, t, 'r', label = 'Train loss')
```

```
mp.legend()
mp.grid()
fig.canvas.draw()
```

-> Seperating the data into test and train from the data

-> Normalizing the input data

-> Converting the class labels using One Hot Encoding

In [3]:

```
(x_train, y_train), (x_test, y_test) = mnist.load_data()
```

```
Downloading data from https://s3.amazonaws.com/img-datasets/mnist.npz
11493376/11490434 [==============================] - 1s 0us/step
```

In [4]:

```
print("The number of data points in training set are:",x_train.shape[0], "and each image is of shape(%d, %d)"%(x_train.shape[1], x_train.shape[2]))
print("The number of data points in test set are:",x_test.shape[0], "and each image is of shape(%d, %d)"%(x_test.shape[1], x_test.shape[2]))

print("The number of class labels in training set are:",x_train.shape[0])
print("The number of class labels in test set are:",x_test.shape[0])
```

```
The number of data points in training set are: 60000 and each image is of shape(28, 28)
The number of data points in test set are: 10000 and each image is of shape(28, 28)
The number of class labels in training set are: 60000
The number of class labels in test set are: 10000
```

In [5]:

```
x_train = x_train.reshape(x_train.shape[0], x_train.shape[1]*x_train.shape[2])
x_test = x_test.reshape(x_test.shape[0], x_test.shape[1]*x_test.shape[2])
print(x_train.shape)
print(x_test.shape)
```

```
(60000, 784)
(10000, 784)
```

In [6]:

```
print("The number of data points in training set are:",x_train.shape[0], "and each image is of shape (%d) " % (x_train.shape[1]))
print("The number of data points in test set are:",x_test.shape[0], "and each image is of shape (%d) " % (x_test.shape[1]))
```

```
The number of data points in training set are: 60000 and each image is of shape (784)
The number of data points in test set are: 10000 and each image is of shape (784)
```

In [7]:

```
print(x_train[50000])
```

```
[   0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0   47  160  195  205
   71   86   13    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0   12  238  254  254  254  254  254  227   84    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0   13  196  176
  127  176  207  236  245  222   23    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0   20  137  254   95    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0   78  254  144    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0   17  200  254
  170    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0   47  218  254  216   29    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0   95  225  254
  245   65    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0   12  128  252  254  236   40    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0  172  254  254
  170   58    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0  207  254  254   65    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0  137
  254  254  251  146   26    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    9  173  224  254  254  230   71    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    8   12  254  254  254  246  104    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0   46  189  254  254
  224    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0   10    0    0    0    0    0   17  175  254  254   25    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0   35  231  156  112   87  186  191  218
  254  254  219    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0  120  255  254  254  254  254  255  254  254  242   67    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0  139  255  254  254  254  254
  255  171   46   24    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    5   71  164  189  174  174   66    4    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0]
```

In [8]:

```
x_train = x_train/255
x_test = x_test/255
print(x_train[50000])
```

```
[0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
```

```
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.18431373 0.62745098 0.76470588 0.80392157
0.27843137 0.3372549  0.05098039 0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.04705882
0.93333333 0.99607843 0.99607843 0.99607843 0.99607843 0.99607843
0.89019608 0.32941176 0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.05098039 0.76862745 0.69019608
0.49803922 0.69019608 0.81176471 0.9254902  0.96078431 0.87058824
0.09019608 0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.07843137 0.5372549  0.99607843 0.37254902 0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.30588235 0.99607843 0.56470588 0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.06666667 0.78431373 0.99607843
0.66666667 0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.18431373 0.85490196 0.99607843 0.84705882 0.11372549 0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.37254902 0.88235294 0.99607843
0.96078431 0.25490196 0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.04705882
0.50196078 0.98823529 0.99607843 0.9254902  0.15686275 0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.6745098  0.99607843 0.99607843
0.66666667 0.22745098 0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
```

```
 0.         0.81176471 0.99607843 0.99607843 0.25490196 0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.5372549
 0.99607843 0.99607843 0.98431373 0.57254902 0.10196078 0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.03529412 0.67843137 0.87843137
 0.99607843 0.99607843 0.90196078 0.27843137 0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.03137255 0.04705882 0.99607843 0.99607843
 0.99607843 0.96470588 0.40784314 0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.18039216 0.74117647 0.99607843 0.99607843
 0.87843137 0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.03921569 0.         0.         0.         0.
 0.         0.06666667 0.68627451 0.99607843 0.99607843 0.09803922
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.1372549  0.90588235
 0.61176471 0.43921569 0.34117647 0.72941176 0.74901961 0.85490196
 0.99607843 0.99607843 0.85882353 0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.47058824 1.         0.99607843 0.99607843
 0.99607843 0.99607843 1.         0.99607843 0.99607843 0.94901961
 0.2627451  0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.54509804 1.         0.99607843 0.99607843 0.99607843 0.99607843
 1.         0.67058824 0.18039216 0.09411765 0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.01960784 0.27843137
 0.64313725 0.74117647 0.68235294 0.68235294 0.25882353 0.01568627
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
```

```
 0.          0.          0.          0.          0.          0.
 0.          0.          0.          0.          0.          0.
 0.          0.          0.          0.          0.          0.
 0.          0.          0.          0.          ]
```

In [9]:

```
print("Class label of sample image :", y_train[50000])
y_train = np_utils.to_categorical(y_train, 10)
y_test = np_utils.to_categorical(y_test, 10)
print("Class label of sample image :", y_train[50000])
```

```
Class label of sample image : 3
Class label of sample image : [0. 0. 0. 1. 0. 0. 0. 0. 0. 0.]
```

In [0]:

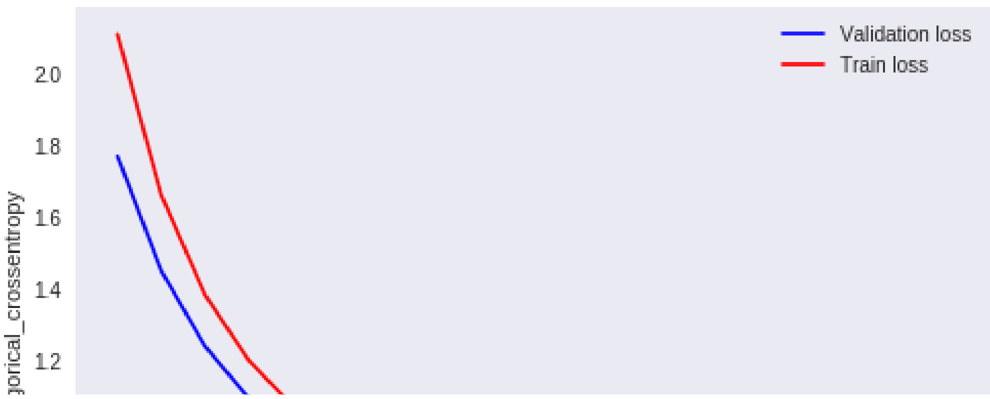
```
from keras.models import Sequential
from keras.layers import Dense,Activation
output_dim = 10
input_shape = 784
batch_size = 1000
number_of_epoch = 20
```

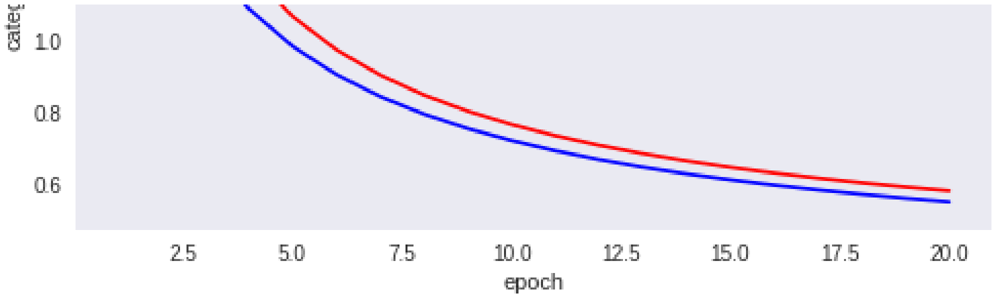
In [15]:

```
model = Sequential()
model.add(Dense(output_dim, input_dim = input_shape, activation = 'softmax'
))
model.compile(optimizer='sgd', loss = 'categorical_crossentropy', metrics =
['accuracy'])
history = model.fit(x_train, y_train, batch_size = batch_size, epochs =
number_of_epoch, validation_data = (x_test, y_test))
score = model.evaluate(x_test,y_test, verbose= 0 )
print("Test Score:", score[0])
print("Accuracy:", score[1])
fig,ax = mp.subplots(1,1)
ax.set_xlabel('epoch')
ax.set_ylabel("categorical_crossentropy")
x = list(range(1, number_of_epoch+1))
vl = history.history['val_loss']
tl = hostory.history['loss']
dynamic_plot(x,vl,tl,ax)
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 1s 12us/step - loss: 2.0231
- acc: 0.3507 - val_loss: 1.7683 - val_acc: 0.5530
Epoch 2/20
60000/60000 [==============================] - 1s 10us/step - loss: 1.6148
- acc: 0.6284 - val_loss: 1.4478 - val_acc: 0.6965
Epoch 3/20
60000/60000 [==============================] - 1s 10us/step - loss: 1.3577
- acc: 0.7160 - val_loss: 1.2371 - val_acc: 0.7566
Epoch 4/20
60000/60000 [==============================] - 1s 11us/step - loss: 1.1847
- acc: 0.7588 - val_loss: 1.0918 - val_acc: 0.7868
Epoch 5/20
60000/60000 [==============================] - 1s 12us/step - loss: 1.0624
- acc: 0.7852 - val_loss: 0.9871 - val_acc: 0.8052
Epoch 6/20
```

```
60000/60000 [==============================] - 1s 12us/step - loss: 0.9721
- acc: 0.8038 - val_loss: 0.9082 - val_acc: 0.8178
Epoch 7/20
60000/60000 [==============================] - 1s 12us/step - loss: 0.9028
- acc: 0.8151 - val_loss: 0.8469 - val_acc: 0.8279
Epoch 8/20
60000/60000 [==============================] - 1s 12us/step - loss: 0.8481
- acc: 0.8231 - val_loss: 0.7977 - val_acc: 0.8370
Epoch 9/20
60000/60000 [==============================] - 1s 11us/step - loss: 0.8036
- acc: 0.8291 - val_loss: 0.7575 - val_acc: 0.8419
Epoch 10/20
56000/60000 [===========================>..] - ETA: 0s - loss: 0.7679 - acc
: 0.83460000/60000 [==============================] - 1s 12us/step - loss:
0.7668 - acc: 0.8349 - val_loss: 0.7239 - val_acc: 0.8462
Epoch 11/20
60000/60000 [==============================] - 1s 12us/step - loss: 0.7358
- acc: 0.8395 - val_loss: 0.6954 - val_acc: 0.8504
Epoch 12/20
60000/60000 [==============================] - 1s 11us/step - loss: 0.7092
- acc: 0.8425 - val_loss: 0.6708 - val_acc: 0.8536
Epoch 13/20
60000/60000 [==============================] - 1s 12us/step - loss: 0.6862
- acc: 0.8456 - val_loss: 0.6495 - val_acc: 0.8569
Epoch 14/20
60000/60000 [==============================] - 1s 11us/step - loss: 0.6660
- acc: 0.8489 - val_loss: 0.6308 - val_acc: 0.8594
Epoch 15/20
60000/60000 [==============================] - 1s 12us/step - loss: 0.6482
- acc: 0.8514 - val_loss: 0.6142 - val_acc: 0.8621
Epoch 16/20
60000/60000 [==============================] - 1s 12us/step - loss: 0.6324
- acc: 0.8543 - val_loss: 0.5993 - val_acc: 0.8639
Epoch 17/20
60000/60000 [==============================] - 1s 11us/step - loss: 0.6181
- acc: 0.8567 - val_loss: 0.5860 - val_acc: 0.8660
Epoch 18/20
60000/60000 [==============================] - 1s 11us/step - loss: 0.6052
- acc: 0.8583 - val_loss: 0.5739 - val_acc: 0.8684
Epoch 19/20
60000/60000 [==============================] - 1s 11us/step - loss: 0.5936
- acc: 0.8598 - val_loss: 0.5628 - val_acc: 0.8700
Epoch 20/20
16000/60000 [=======>......................] - ETA: 0s - loss: 0.5892 - acc
: 0.861960000/60000 [==============================] - 1s 12us/step - loss:
0.5829 - acc: 0.8614 - val_loss: 0.5527 - val_acc: 0.8710
Test Score: 0.552729869556427
Accuracy: 0.871
```





MODEL 1 : INPUT(784) - SIGMOID(640) - SIGMOID(320) - SIGMOID(120) - OUTPUT(SOFTMAX(10)) WITH SGD OPTIMIZER

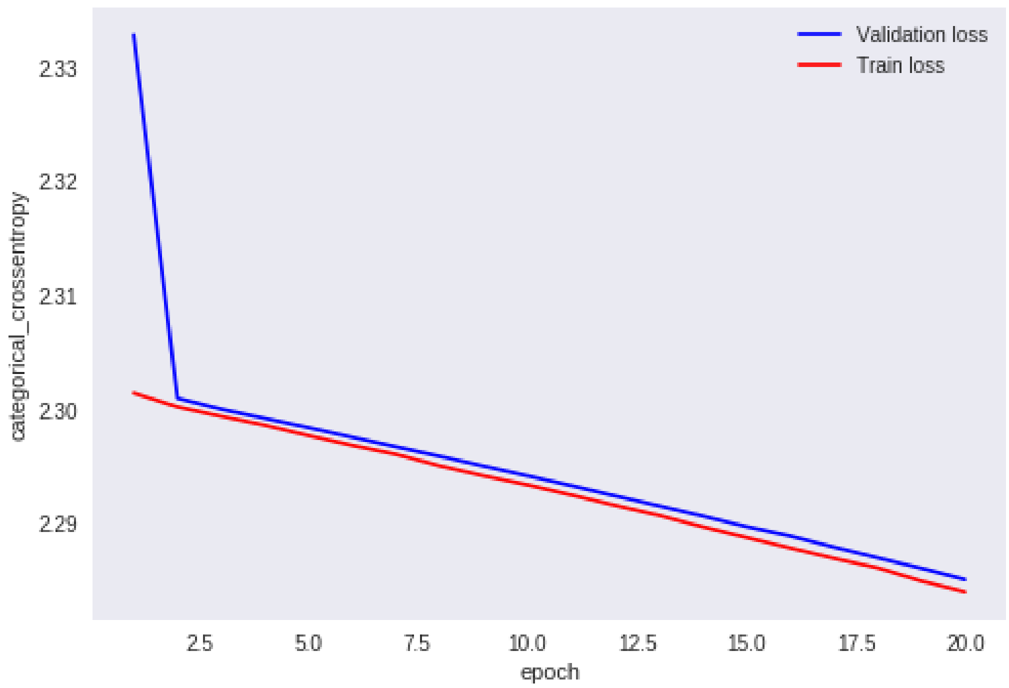
In [22]:

```
sigmoid_model = Sequential()
sigmoid_model.add(Dense(640, activation = 'sigmoid', input_shape =
(input_shape,)))
sigmoid_model.add(Dense(320, activation = 'sigmoid'))
sigmoid_model.add(Dense(120, activation = 'sigmoid'))
sigmoid_model.add(Dense(output_dim, activation  = 'softmax'))
sigmoid_model.summary()
sigmoid_model.compile(optimizer = 'sgd', loss = 'categorical_crossentropy',
metrics = ['accuracy'])
history = sigmoid_model.fit(x_train, y_train, batch_size= batch_size, epoch
s= number_of_epoch, validation_data=(x_test, y_test))
score = sigmoid_model.evaluate(x_test, y_test)
print("Test score:", score[0])
print("Test Accuracy:", score[1])
fig,ax = mp.subplots(1,1)
ax.set_xlabel("epoch")
ax.set_ylabel("categorical_crossentropy")
x = list(range(1, number_of_epoch+1))
tl = history.history['loss']
vl = history.history['val_loss']
dynamic_plot(x,tl,vl,ax)
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_22 (Dense)             (None, 640)               502400    
_________________________________________________________________
dense_23 (Dense)             (None, 320)               205120    
_________________________________________________________________
dense_24 (Dense)             (None, 120)               38520     
_________________________________________________________________
dense_25 (Dense)             (None, 10)                1210      
=================================================================
Total params: 747,250
Trainable params: 747,250
Non-trainable params: 0
_________________________________________________________________
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 4s 67us/step - loss: 2.3329
- acc: 0.1124 - val_loss: 2.3015 - val_acc: 0.1135
Epoch 2/20
46000/60000 [======================>.......] - ETA: 1s - loss: 2.3011 - acc
```

```
: 0.113060000/60000 [==============================] - 5s 83us/step - loss:
2.3010 - acc: 0.1124 - val_loss: 2.3003 - val_acc: 0.1135
Epoch 3/20
60000/60000 [==============================] - 5s 84us/step - loss: 2.3001
- acc: 0.1124 - val_loss: 2.2994 - val_acc: 0.1135
Epoch 4/20
60000/60000 [==============================] - 5s 84us/step - loss: 2.2992
- acc: 0.1124 - val_loss: 2.2987 - val_acc: 0.1135
Epoch 5/20
60000/60000 [==============================] - 5s 84us/step - loss: 2.2984
- acc: 0.1124 - val_loss: 2.2977 - val_acc: 0.1135
Epoch 6/20
54000/60000 [==========================>...] - ETA: 0s - loss: 2.2977 - acc
: 0.112560000/60000 [==============================] - 5s 84us/step - loss:
2.2976 - acc: 0.1124 - val_loss: 2.2969 - val_acc: 0.1135
Epoch 7/20
60000/60000 [==============================] - 5s 83us/step - loss: 2.2968
- acc: 0.1124 - val_loss: 2.2961 - val_acc: 0.1135
Epoch 8/20
60000/60000 [==============================] - 5s 84us/step - loss: 2.2959
- acc: 0.1124 - val_loss: 2.2951 - val_acc: 0.1135
Epoch 9/20
60000/60000 [==============================] - 5s 83us/step - loss: 2.2951
- acc: 0.1124 - val_loss: 2.2942 - val_acc: 0.1135
Epoch 10/20
55000/60000 [==========================>...] - ETA: 0s - loss: 2.2942 - acc
: 0.112960000/60000 [==============================] - 5s 83us/step - loss:
2.2942 - acc: 0.1124 - val_loss: 2.2934 - val_acc: 0.1135
Epoch 11/20
60000/60000 [==============================] - 5s 83us/step - loss: 2.2934
- acc: 0.1124 - val_loss: 2.2925 - val_acc: 0.1135
Epoch 12/20
60000/60000 [==============================] - 5s 81us/step - loss: 2.2925
- acc: 0.1125 - val_loss: 2.2916 - val_acc: 0.1135
Epoch 13/20
60000/60000 [==============================] - 5s 84us/step - loss: 2.2916
- acc: 0.1125 - val_loss: 2.2908 - val_acc: 0.1135
Epoch 14/20
54000/60000 [==========================>...] - ETA: 0s - loss: 2.2907 - acc
: 0.115260000/60000 [==============================] - 5s 84us/step - loss:
2.2907 - acc: 0.1153 - val_loss: 2.2897 - val_acc: 0.1135
Epoch 15/20
60000/60000 [==============================] - 5s 84us/step - loss: 2.2898
- acc: 0.1124 - val_loss: 2.2888 - val_acc: 0.1135
Epoch 16/20
60000/60000 [==============================] - 5s 84us/step - loss: 2.2889
- acc: 0.1124 - val_loss: 2.2879 - val_acc: 0.1135
Epoch 17/20
60000/60000 [==============================] - 5s 84us/step - loss: 2.2880
- acc: 0.1139 - val_loss: 2.2870 - val_acc: 0.1135
Epoch 18/20
54000/60000 [==========================>...] - ETA: 0s - loss: 2.2871 - acc
: 0.112960000/60000 [==============================] - 5s 83us/step - loss:
2.2870 - acc: 0.1125 - val_loss: 2.2861 - val_acc: 0.1135
Epoch 19/20
60000/60000 [==============================] - 5s 83us/step - loss: 2.2861
- acc: 0.1140 - val_loss: 2.2850 - val_acc: 0.1135
Epoch 20/20
60000/60000 [==============================] - 5s 83us/step - loss: 2.2851
- acc: 0.1140 - val_loss: 2.2840 - val_acc: 0.1142
10000/10000 [==============================] - 1s 85us/step
```

```
10000/10000 [==============================] - 1s 85us/step
Test score: 2.2840435642242434
Test Accuracy: 0.1142
```



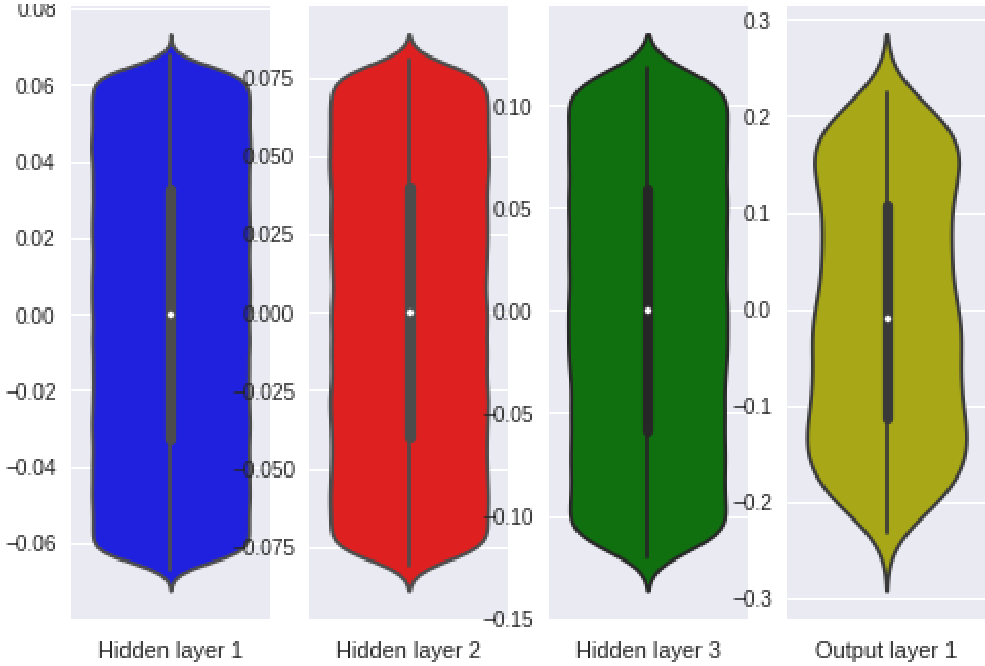
In [28]:

```
after_weights  = sigmoid_model.get_weights()
h1_w = after_weights[0].flatten().reshape(-1,1)
h2_w = after_weights[2].flatten().reshape(-1,1)
h3_w = after_weights[4].flatten().reshape(-1,1)
out_w = after_weights[6].flatten().reshape(-1,1)
fig = mp.figure()
mp.subplot(1,4,1)
mp.title("Weights")
ax = s.violinplot(y  = h1_w, color='b')
mp.xlabel('Hidden layer 1')
mp.subplot(1,4,2)
mp.title("Weights")
ax = s.violinplot(y  = h2_w, color='r')
mp.xlabel('Hidden layer 2')
mp.subplot(1,4,3)
mp.title("Weights")
ax = s.violinplot(y  = h3_w, color='g')
mp.xlabel('Hidden layer 3')
mp.subplot(1,4,4)
mp.title("Weights")
ax = s.violinplot(y  = out_w, color='y')
mp.xlabel('Output layer 1')
```

```
/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)
```

Out[28]:

```
Text(0.5,0,'Output layer 1')
```



MODEL 1 WITH ADAM OPTIMIZER

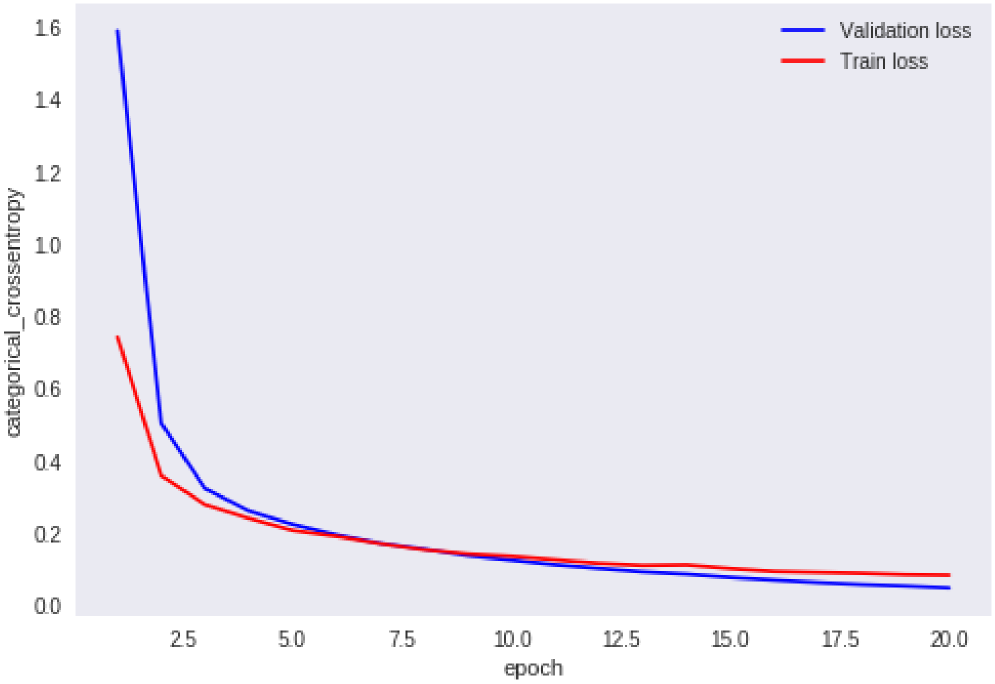
In [29]:

```
sigmoid_model = Sequential()
sigmoid_model.add(Dense(640, activation = 'sigmoid', input_shape =
(input_shape,)))
sigmoid_model.add(Dense(320, activation = 'sigmoid'))
sigmoid_model.add(Dense(120, activation = 'sigmoid'))
sigmoid_model.add(Dense(output_dim, activation  = 'softmax'))
sigmoid_model.summary()
sigmoid_model.compile(optimizer = 'adam', loss = 'categorical_crossentropy'
, metrics = ['accuracy'])
history = sigmoid_model.fit(x_train, y_train, batch_size= batch_size, epoch
s= number_of_epoch, validation_data=(x_test, y_test))
score = sigmoid_model.evaluate(x_test, y_test)
print("Test score:", score[0])
print("Test Accuracy:", score[1])
fig,ax = mp.subplots(1,1)
ax.set_xlabel("epoch")
ax.set_ylabel("categorical_crossentropy")
x = list(range(1, number_of_epoch+1))
tl = history.history['loss']
vl = history.history['val_loss']
dynamic_plot(x,tl,vl,ax)
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_26 (Dense)             (None, 640)               502400
_________________________________________________________________
dense_27 (Dense)             (None, 320)               205120
_________________________________________________________________
dense_28 (Dense)             (None, 120)               38520
_________________________________________________________________
dense_29 (Dense)             (None, 10)                1210
=================================================================
Total params: 747,250
```

```
Trainable params: 747,250
Non-trainable params: 0
_________________________________________________________________
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 6s 93us/step - loss: 1.5910
- acc: 0.5501 - val_loss: 0.7431 - val_acc: 0.8333
Epoch 2/20
32000/60000 [===============>..............] - ETA: 2s - loss: 0.5845 - acc
: 0.862860000/60000 [==============================] - 5s 88us/step - loss:
0.5037 - acc: 0.8758 - val_loss: 0.3590 - val_acc: 0.9047
Epoch 3/20
60000/60000 [==============================] - 5s 88us/step - loss: 0.3233
- acc: 0.9100 - val_loss: 0.2785 - val_acc: 0.9209
Epoch 4/20
60000/60000 [==============================] - 5s 86us/step - loss: 0.2612
- acc: 0.9251 - val_loss: 0.2406 - val_acc: 0.9305
Epoch 5/20
60000/60000 [==============================] - 5s 88us/step - loss: 0.2239
- acc: 0.9351 - val_loss: 0.2070 - val_acc: 0.9392
Epoch 6/20
52000/60000 [=========================>....] - ETA: 0s - loss: 0.1949 - acc
: 0.943960000/60000 [==============================] - 5s 86us/step - loss:
0.1946 - acc: 0.9439 - val_loss: 0.1908 - val_acc: 0.9421
Epoch 7/20
60000/60000 [==============================] - 5s 87us/step - loss: 0.1715
- acc: 0.9506 - val_loss: 0.1707 - val_acc: 0.9495
Epoch 8/20
60000/60000 [==============================] - 5s 89us/step - loss: 0.1557
- acc: 0.9547 - val_loss: 0.1538 - val_acc: 0.9543
Epoch 9/20
60000/60000 [==============================] - 5s 88us/step - loss: 0.1371
- acc: 0.9601 - val_loss: 0.1420 - val_acc: 0.9570
Epoch 10/20
55000/60000 [==========================>...] - ETA: 0s - loss: 0.1248 - acc
: 0.963860000/60000 [==============================] - 5s 89us/step - loss:
0.1248 - acc: 0.9638 - val_loss: 0.1355 - val_acc: 0.9599
Epoch 11/20
60000/60000 [==============================] - 5s 88us/step - loss: 0.1121
- acc: 0.9676 - val_loss: 0.1258 - val_acc: 0.9625
Epoch 12/20
60000/60000 [==============================] - 5s 88us/step - loss: 0.1019
- acc: 0.9710 - val_loss: 0.1160 - val_acc: 0.9649
Epoch 13/20
60000/60000 [==============================] - 5s 88us/step - loss: 0.0924
- acc: 0.9739 - val_loss: 0.1103 - val_acc: 0.9668
Epoch 14/20
54000/60000 [==========================>...] - ETA: 0s - loss: 0.0863 - acc
: 0.975360000/60000 [==============================] - 5s 86us/step - loss:
0.0860 - acc: 0.9754 - val_loss: 0.1118 - val_acc: 0.9656
Epoch 15/20
60000/60000 [==============================] - 5s 88us/step - loss: 0.0769
- acc: 0.9783 - val_loss: 0.1016 - val_acc: 0.9700
Epoch 16/20
60000/60000 [==============================] - 5s 87us/step - loss: 0.0695
- acc: 0.9803 - val_loss: 0.0936 - val_acc: 0.9705
Epoch 17/20
60000/60000 [==============================] - 5s 87us/step - loss: 0.0629
- acc: 0.9826 - val_loss: 0.0909 - val_acc: 0.9724
Epoch 18/20
```

```
54000/60000 [==========================>...] - ETA: 0s - loss: 0.0570 - acc
: 0.984260000/60000 [==============================] - 5s 87us/step - loss:
0.0574 - acc: 0.9840 - val_loss: 0.0885 - val_acc: 0.9735
Epoch 19/20
60000/60000 [==============================] - 5s 88us/step - loss: 0.0534
- acc: 0.9842 - val_loss: 0.0845 - val_acc: 0.9749
Epoch 20/20
60000/60000 [==============================] - 5s 87us/step - loss: 0.0481
- acc: 0.9867 - val_loss: 0.0832 - val_acc: 0.9739
10000/10000 [==============================] - 1s 88us/step
Test score: 0.08319248105995357
Test Accuracy: 0.9739
```



In [30]:

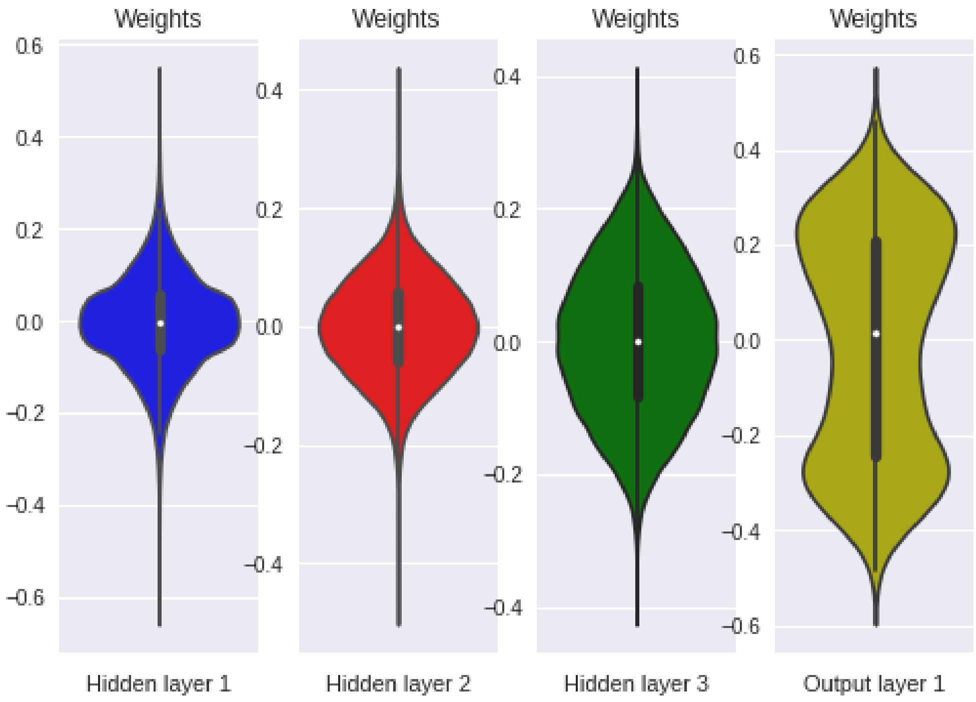
```
after_weights  = sigmoid_model.get_weights()
h1_w = after_weights[0].flatten().reshape(-1,1)
h2_w = after_weights[2].flatten().reshape(-1,1)
h3_w = after_weights[4].flatten().reshape(-1,1)
out_w = after_weights[6].flatten().reshape(-1,1)
fig = mp.figure()
mp.subplot(1,4,1)
mp.title("Weights")
ax = s.violinplot(y  = h1_w, color='b')
mp.xlabel('Hidden layer 1')
mp.subplot(1,4,2)
mp.title("Weights")
ax = s.violinplot(y  = h2_w, color='r')
mp.xlabel('Hidden layer 2')
mp.subplot(1,4,3)
mp.title("Weights")
ax = s.violinplot(y  = h3_w, color='g')
mp.xlabel('Hidden layer 3')
mp.subplot(1,4,4)
mp.title("Weights")
ax = s.violinplot(y  = out_w, color='y')
mp.xlabel('Output layer 1')
```

```
/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.
```

```
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)
```

Out[30]:

```
Text(0.5,0,'Output layer 1')
```



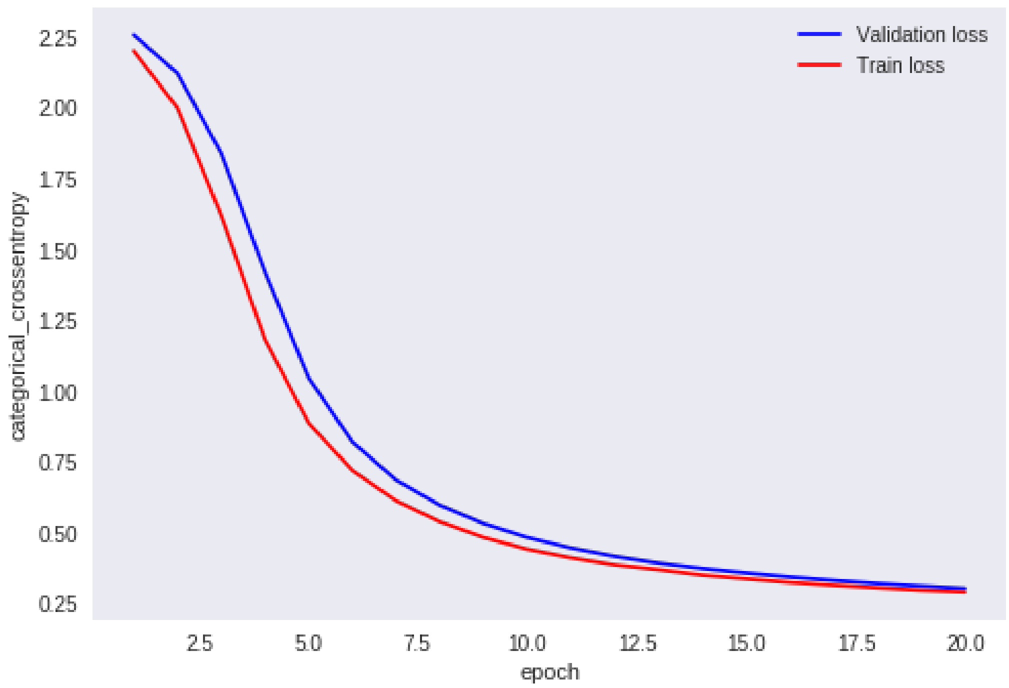
MODEL 2 : INPUT(784) - RELU(400) - RELU(300) - RELU(200) - RELU(100) - RELU(50) - OUTPUT(SOFTMAX(10)) WITH SGD OPTIMIZER

In [32]:

```
relu_model = Sequential()
relu_model.add(Dense(400, activation = 'relu', input_shape =
(input_shape,)))
relu_model.add(Dense(300, activation = 'relu'))
relu_model.add(Dense(200, activation = 'relu'))
relu_model.add(Dense(100, activation = 'relu'))
relu_model.add(Dense(50, activation = 'relu'))
relu_model.add(Dense(output_dim, activation  = 'softmax'))
relu_model.summary()
relu_model.compile(optimizer = 'sgd', loss = 'categorical_crossentropy', me
trics = ['accuracy'])
history = relu_model.fit(x_train, y_train, batch_size= batch_size, epochs=
number_of_epoch, validation_data=(x_test, y_test))
score = relu_model.evaluate(x_test, y_test)
print("Test score:", score[0])
print("Test Accuracy:", score[1])
fig,ax = mp.subplots(1,1)
ax.set_xlabel("epoch")
ax.set_ylabel("categorical_crossentropy")
x = list(range(1, number_of_epoch+1))
tl = history.history['loss']
vl = history.history['val_loss']
dynamic_plot(x,tl,vl,ax)
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_36 (Dense)             (None, 400)               314000    
_________________________________________________________________
dense_37 (Dense)             (None, 300)               120300    
_________________________________________________________________
dense_38 (Dense)             (None, 200)               60200     
_________________________________________________________________
dense_39 (Dense)             (None, 100)               20100     
_________________________________________________________________
dense_40 (Dense)             (None, 50)                5050      
_________________________________________________________________
dense_41 (Dense)             (None, 10)                510       
=================================================================
Total params: 520,160
Trainable params: 520,160
Non-trainable params: 0
_________________________________________________________________
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 3s 57us/step - loss: 2.2574
- acc: 0.1780 - val_loss: 2.2012 - val_acc: 0.2676
Epoch 2/20
30000/60000 [==============>...............] - ETA: 1s - loss: 2.1704 - acc
: 0.303260000/60000 [==============================] - 4s 65us/step - loss:
2.1221 - acc: 0.3541 - val_loss: 1.9996 - val_acc: 0.4645
Epoch 3/20
60000/60000 [==============================] - 4s 67us/step - loss: 1.8404
- acc: 0.5272 - val_loss: 1.6208 - val_acc: 0.6093
Epoch 4/20
60000/60000 [==============================] - 4s 65us/step - loss: 1.4216
- acc: 0.6635 - val_loss: 1.1830 - val_acc: 0.7193
Epoch 5/20
60000/60000 [==============================] - 4s 66us/step - loss: 1.0470
- acc: 0.7372 - val_loss: 0.8876 - val_acc: 0.7725
Epoch 6/20
52000/60000 [=========================>....] - ETA: 0s - loss: 0.8296 - acc
: 0.781860000/60000 [==============================] - 4s 67us/step - loss:
0.8211 - acc: 0.7838 - val_loss: 0.7202 - val_acc: 0.8188
Epoch 7/20
60000/60000 [==============================] - 4s 67us/step - loss: 0.6864
- acc: 0.8180 - val_loss: 0.6131 - val_acc: 0.8403
Epoch 8/20
60000/60000 [==============================] - 4s 66us/step - loss: 0.5975
- acc: 0.8404 - val_loss: 0.5393 - val_acc: 0.8584
Epoch 9/20
60000/60000 [==============================] - 4s 67us/step - loss: 0.5327
- acc: 0.8571 - val_loss: 0.4838 - val_acc: 0.8737
Epoch 10/20
55000/60000 [==========================>...] - ETA: 0s - loss: 0.4866 - acc
: 0.868960000/60000 [==============================] - 4s 66us/step - loss:
0.4837 - acc: 0.8701 - val_loss: 0.4418 - val_acc: 0.8812
Epoch 11/20
60000/60000 [==============================] - 4s 66us/step - loss: 0.4461
- acc: 0.8789 - val_loss: 0.4117 - val_acc: 0.8875
Epoch 12/20
60000/60000 [==============================] - 4s 67us/step - loss: 0.4167
- acc: 0.8861 - val_loss: 0.3867 - val_acc: 0.8917
Epoch 13/20
60000/60000 [==============================] - 4s 68us/step - loss: 0.3932
```

```
- acc: 0.8921 - val_loss: 0.3696 - val_acc: 0.8978
Epoch 14/20
53000/60000 [=========================>....] - ETA: 0s - loss: 0.3778 - acc
: 0.895660000/60000 [==============================] - 4s 68us/step - loss:
0.3740 - acc: 0.8968 - val_loss: 0.3505 - val_acc: 0.9021
Epoch 15/20
60000/60000 [==============================] - 4s 67us/step - loss: 0.3584
- acc: 0.8999 - val_loss: 0.3376 - val_acc: 0.9054
Epoch 16/20
60000/60000 [==============================] - 4s 67us/step - loss: 0.3443
- acc: 0.9042 - val_loss: 0.3249 - val_acc: 0.9086
Epoch 17/20
60000/60000 [==============================] - 4s 68us/step - loss: 0.3322
- acc: 0.9070 - val_loss: 0.3150 - val_acc: 0.9110
Epoch 18/20
51000/60000 [========================>.....] - ETA: 0s - loss: 0.3216 - acc
: 0.91060000/60000 [==============================] - 4s 67us/step - loss:
0.3215 - acc: 0.9097 - val_loss: 0.3062 - val_acc: 0.9126
Epoch 19/20
60000/60000 [==============================] - 4s 67us/step - loss: 0.3122
- acc: 0.9118 - val_loss: 0.2976 - val_acc: 0.9160
Epoch 20/20
60000/60000 [==============================] - 4s 68us/step - loss: 0.3036
- acc: 0.9145 - val_loss: 0.2918 - val_acc: 0.9172
10000/10000 [==============================] - 1s 81us/step
Test score: 0.2917701820760965
Test Accuracy: 0.9172
```



In [38]:

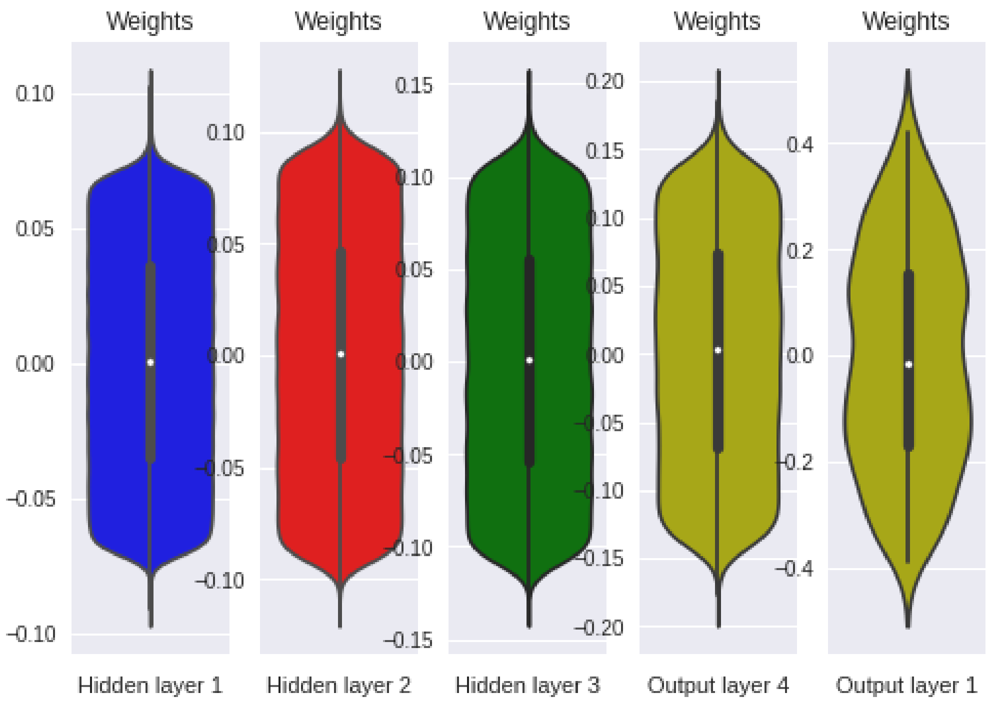
```
after_weights  = relu_model.get_weights()
h1_w = after_weights[0].flatten().reshape(-1,1)
h2_w = after_weights[2].flatten().reshape(-1,1)
h3_w = after_weights[4].flatten().reshape(-1,1)
h4_w = after_weights[6].flatten().reshape(-1,1)
out_w = after_weights[10].flatten().reshape(-1,1)
fig = mp.figure()
mp.subplot(1,5,1)
mp.title("Weights")
```

```
ax = s.violinplot(y  = h1_w, color='b')
mp.xlabel('Hidden layer 1')
mp.subplot(1,5,2)
mp.title("Weights")
ax = s.violinplot(y  = h2_w, color='r')
mp.xlabel('Hidden layer 2')
mp.subplot(1,5,3)
mp.title("Weights")
ax = s.violinplot(y  = h3_w, color='g')
mp.xlabel('Hidden layer 3')
mp.subplot(1,5,4)
mp.title("Weights")
ax = s.violinplot(y  = h4_w, color='y')
mp.xlabel('Output layer 4')
mp.subplot(1,5,5)
mp.title("Weights")
ax = s.violinplot(y  = out_w, color='y')
mp.xlabel('Output layer 1')
```

```
/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)
```

Out[38]:

```
Text(0.5,0,'Output layer 1')
```



MODEL 2 WITH ADAM OPTIMIZER

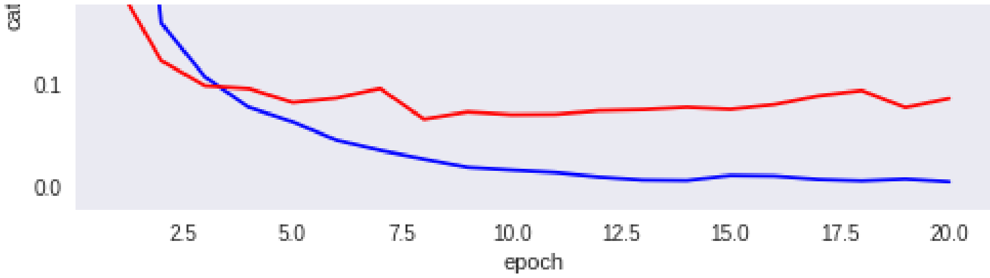
In [39]:

```
relu_model = Sequential()
relu_model.add(Dense(400, activation = 'relu', input_shape =
(input_shape,)))
relu_model.add(Dense(300, activation = 'relu'))
```

```
relu_model.add(Dense(200, activation = 'relu'))
relu_model.add(Dense(100, activation = 'relu'))
relu_model.add(Dense(50, activation = 'relu'))
relu_model.add(Dense(output_dim, activation  = 'softmax'))
relu_model.summary()
relu_model.compile(optimizer = 'adam', loss = 'categorical_crossentropy', m
etrics = ['accuracy'])
history = relu_model.fit(x_train, y_train, batch_size= batch_size, epochs=
number_of_epoch, validation_data=(x_test, y_test))
score = relu_model.evaluate(x_test, y_test)
print("Test score:", score[0])
print("Test Accuracy:", score[1])
fig,ax = mp.subplots(1,1)
ax.set_xlabel("epoch")
ax.set_ylabel("categorical_crossentropy")
x = list(range(1, number_of_epoch+1))
tl = history.history['loss']
vl = history.history['val_loss']
dynamic_plot(x,tl,vl,ax)
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_42 (Dense)             (None, 400)               314000    
_________________________________________________________________
dense_43 (Dense)             (None, 300)               120300    
_________________________________________________________________
dense_44 (Dense)             (None, 200)               60200     
_________________________________________________________________
dense_45 (Dense)             (None, 100)               20100     
_________________________________________________________________
dense_46 (Dense)             (None, 50)                5050      
_________________________________________________________________
dense_47 (Dense)             (None, 10)                510       
=================================================================
Total params: 520,160
Trainable params: 520,160
Non-trainable params: 0
_________________________________________________________________
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 4s 66us/step - loss: 0.5550
- acc: 0.8397 - val_loss: 0.1981 - val_acc: 0.9404
Epoch 2/20
26000/60000 [============>.................] - ETA: 2s - loss: 0.1810 - acc
: 0.946060000/60000 [==============================] - 4s 68us/step - loss:
0.1605 - acc: 0.9523 - val_loss: 0.1235 - val_acc: 0.9629
Epoch 3/20
60000/60000 [==============================] - 4s 70us/step - loss: 0.1075
- acc: 0.9684 - val_loss: 0.0986 - val_acc: 0.9695
Epoch 4/20
60000/60000 [==============================] - 4s 71us/step - loss: 0.0775
- acc: 0.9766 - val_loss: 0.0958 - val_acc: 0.9699
Epoch 5/20
60000/60000 [==============================] - 4s 70us/step - loss: 0.0631
- acc: 0.9812 - val_loss: 0.0824 - val_acc: 0.9745
Epoch 6/20
45000/60000 [=====================>........] - ETA: 0s - loss: 0.0429 - acc
: 0.987260000/60000 [==============================] - 4s 70us/step - loss:
0.0451 - acc: 0.9863 - val_loss: 0.0867 - val_acc: 0.9731
Epoch 7/20
```

```
Epoch 7/20
60000/60000 [==============================] - 4s 71us/step - loss: 0.0349
- acc: 0.9900 - val_loss: 0.0960 - val_acc: 0.9699
Epoch 8/20
60000/60000 [==============================] - 4s 70us/step - loss: 0.0263
- acc: 0.9924 - val_loss: 0.0657 - val_acc: 0.9796
Epoch 9/20
60000/60000 [==============================] - 4s 71us/step - loss: 0.0181
- acc: 0.9947 - val_loss: 0.0729 - val_acc: 0.9798
Epoch 10/20
45000/60000 [=====================>........] - ETA: 1s - loss: 0.0152 - acc
: 0.995960000/60000 [==============================] - 4s 71us/step - loss:
0.0154 - acc: 0.9957 - val_loss: 0.0701 - val_acc: 0.9791
Epoch 11/20
60000/60000 [==============================] - 4s 70us/step - loss: 0.0131
- acc: 0.9960 - val_loss: 0.0704 - val_acc: 0.9802
Epoch 12/20
60000/60000 [==============================] - 4s 70us/step - loss: 0.0086
- acc: 0.9976 - val_loss: 0.0742 - val_acc: 0.9796
Epoch 13/20
60000/60000 [==============================] - 4s 71us/step - loss: 0.0057
- acc: 0.9987 - val_loss: 0.0752 - val_acc: 0.9826
Epoch 14/20
40000/60000 [===================>..........] - ETA: 1s - loss: 0.0047 - acc
: 0.998860000/60000 [==============================] - 4s 70us/step - loss:
0.0053 - acc: 0.9986 - val_loss: 0.0775 - val_acc: 0.9810
Epoch 15/20
60000/60000 [==============================] - 4s 71us/step - loss: 0.0102
- acc: 0.9969 - val_loss: 0.0755 - val_acc: 0.9821
Epoch 16/20
60000/60000 [==============================] - 4s 71us/step - loss: 0.0097
- acc: 0.9970 - val_loss: 0.0802 - val_acc: 0.9793
Epoch 17/20
60000/60000 [==============================] - 4s 71us/step - loss: 0.0063
- acc: 0.9979 - val_loss: 0.0887 - val_acc: 0.9802
Epoch 18/20
41000/60000 [===================>..........] - ETA: 1s - loss: 0.0049 - acc
: 0.998660000/60000 [==============================] - 4s 70us/step - loss:
0.0050 - acc: 0.9985 - val_loss: 0.0940 - val_acc: 0.9794
Epoch 19/20
60000/60000 [==============================] - 4s 71us/step - loss: 0.0068
- acc: 0.9978 - val_loss: 0.0773 - val_acc: 0.9827
Epoch 20/20
60000/60000 [==============================] - 4s 71us/step - loss: 0.0040
- acc: 0.9987 - val_loss: 0.0863 - val_acc: 0.9804
10000/10000 [==============================] - 1s 80us/step
Test score: 0.08630873851410388
Test Accuracy: 0.9804
```



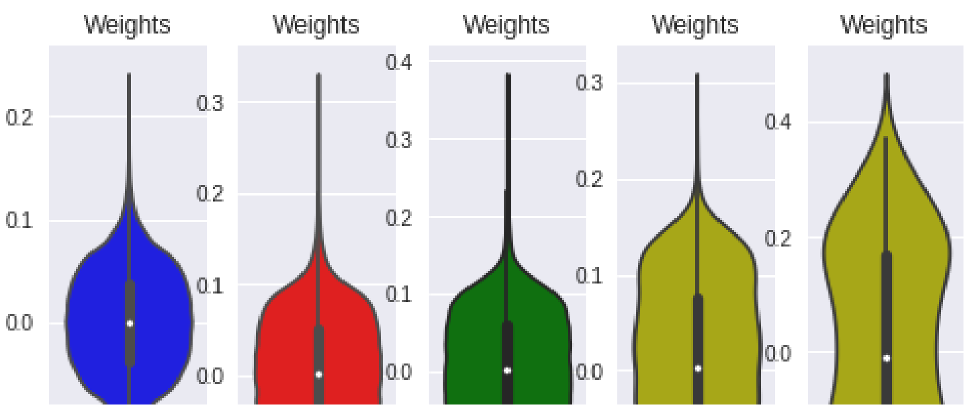
In [40]:

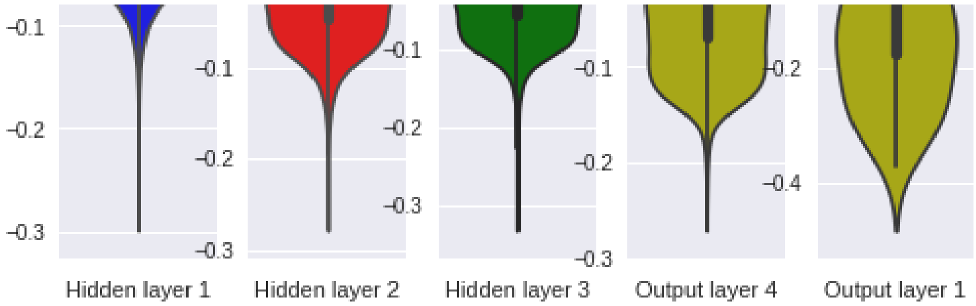
```
after_weights  = relu_model.get_weights()
h1_w = after_weights[0].flatten().reshape(-1,1)
h2_w = after_weights[2].flatten().reshape(-1,1)
h3_w = after_weights[4].flatten().reshape(-1,1)
h4_w = after_weights[6].flatten().reshape(-1,1)
out_w = after_weights[10].flatten().reshape(-1,1)
fig = mp.figure()
mp.subplot(1,5,1)
mp.title("Weights")
ax = s.violinplot(y  = h1_w, color='b')
mp.xlabel('Hidden layer 1')
mp.subplot(1,5,2)
mp.title("Weights")
ax = s.violinplot(y  = h2_w, color='r')
mp.xlabel('Hidden layer 2')
mp.subplot(1,5,3)
mp.title("Weights")
ax = s.violinplot(y  = h3_w, color='g')
mp.xlabel('Hidden layer 3')
mp.subplot(1,5,4)
mp.title("Weights")
ax = s.violinplot(y  = h4_w, color='y')
mp.xlabel('Output layer 4')
mp.subplot(1,5,5)
mp.title("Weights")
ax = s.violinplot(y  = out_w, color='y')
mp.xlabel('Output layer 1')
```

```
/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)
```

Out[40]:

```
Text(0.5,0,'Output layer 1')
```





MODEL 3: INPUT(784) - SIGMOID(160) - SIGMOID(80) - SIGMOID(40) - OUTPUT(SOFTMAX(10)) WITH SGD OPTIMIZER + BATCH NORMALIZATION ON HIDDEN LAYERS

-> Uniform Initialization of weights for Sigmoid Activation Functions

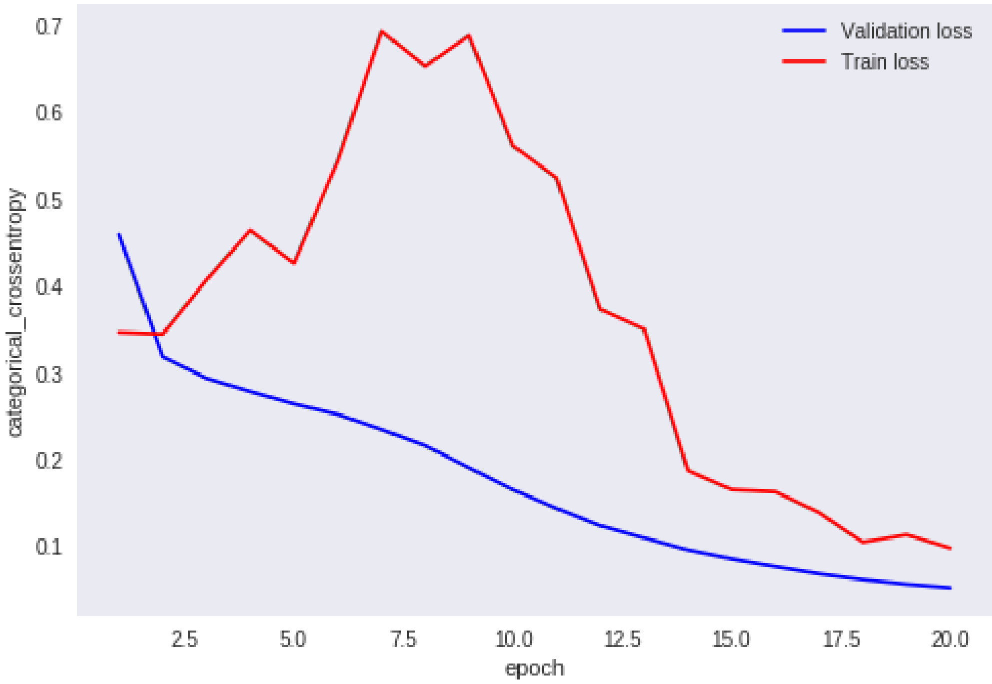
In [41]:

```
from keras.layers.normalization import BatchNormalization
batch_model = Sequential()
batch_model.add(Dense(160, activation = 'sigmoid', input_shape =
(input_shape,), kernel_initializer= RandomNormal(mean = 0, stddev= 0.00625,
seed= None)))
batch_model.add(BatchNormalization())
batch_model.add(Dense(80, activation = 'sigmoid', kernel_initializer= Rando
mNormal(mean = 0, stddev= 0.0125, seed = None)))
batch_model.add(BatchNormalization())
batch_model.add(Dense(40, activation = 'sigmoid', kernel_initializer= Rando
mNormal(mean = 0, stddev= 0.025, seed = None)))
batch_model.add(BatchNormalization())
batch_model.add(Dense(output_dim, activation  = 'softmax'))
batch_model.summary()
batch_model.compile(optimizer = 'adam', loss = 'categorical_crossentropy',
metrics = ['accuracy'])
history = batch_model.fit(x_train, y_train, batch_size= batch_size, epochs=
number_of_epoch, validation_data=(x_test, y_test))
score = batch_model.evaluate(x_test, y_test)
print("Test score:", score[0])
print("Test Accuracy:", score[1])
fig,ax = mp.subplots(1,1)
ax.set_xlabel("epoch")
ax.set_ylabel("categorical_crossentropy")
x = list(range(1, number_of_epoch+1))
tl = history.history['loss']
vl = history.history['val_loss']
dynamic_plot(x,tl,vl,ax)
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_48 (Dense)             (None, 160)               125600
_________________________________________________________________
batch_normalization_1 (Batch (None, 160)               640
_________________________________________________________________
dense_49 (Dense)             (None, 80)                12880
```

```
_________________________________________________________________
batch_normalization_2 (Batch (None, 80)                320       
_________________________________________________________________
dense_50 (Dense)             (None, 40)                3240      
_________________________________________________________________
batch_normalization_3 (Batch (None, 40)                160       
_________________________________________________________________
dense_51 (Dense)             (None, 10)                410       
=================================================================
Total params: 143,250
Trainable params: 142,690
Non-trainable params: 560
_________________________________________________________________
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.4595 
- acc: 0.8723 - val_loss: 0.3469 - val_acc: 0.8995
Epoch 2/20
60000/60000 [==============================] - 2s 38us/step - loss: 0.3187 
- acc: 0.9132 - val_loss: 0.3449 - val_acc: 0.8985
Epoch 3/20
 3000/60000 [>.............................] - ETA: 2s - loss: 0.2885 - acc
: 0.918360000/60000 [==============================] - 2s 38us/step - loss: 
0.2939 - acc: 0.9183 - val_loss: 0.4073 - val_acc: 0.8800
Epoch 4/20
60000/60000 [==============================] - 2s 38us/step - loss: 0.2787 
- acc: 0.9218 - val_loss: 0.4644 - val_acc: 0.8578
Epoch 5/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.2645 
- acc: 0.9253 - val_loss: 0.4265 - val_acc: 0.8703
Epoch 6/20
60000/60000 [==============================] - 2s 37us/step - loss: 0.2523 
- acc: 0.9290 - val_loss: 0.5447 - val_acc: 0.8255
Epoch 7/20
60000/60000 [==============================] - 2s 37us/step - loss: 0.2349 
- acc: 0.9339 - val_loss: 0.6936 - val_acc: 0.7750
Epoch 8/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.2165 
- acc: 0.9379 - val_loss: 0.6534 - val_acc: 0.7799
Epoch 9/20
33000/60000 [===============>..............] - ETA: 0s - loss: 0.1940 - acc
: 0.942860000/60000 [==============================] - 2s 37us/step - loss: 
0.1909 - acc: 0.9445 - val_loss: 0.6887 - val_acc: 0.7607
Epoch 10/20
60000/60000 [==============================] - 2s 38us/step - loss: 0.1658 
- acc: 0.9517 - val_loss: 0.5620 - val_acc: 0.7912
Epoch 11/20
60000/60000 [==============================] - 2s 38us/step - loss: 0.1440 
- acc: 0.9579 - val_loss: 0.5247 - val_acc: 0.8170
Epoch 12/20
60000/60000 [==============================] - 2s 38us/step - loss: 0.1243 
- acc: 0.9629 - val_loss: 0.3735 - val_acc: 0.8604
Epoch 13/20
60000/60000 [==============================] - 2s 38us/step - loss: 0.1101 
- acc: 0.9664 - val_loss: 0.3507 - val_acc: 0.8663
Epoch 14/20
60000/60000 [==============================] - 2s 38us/step - loss: 0.0961 
- acc: 0.9708 - val_loss: 0.1877 - val_acc: 0.9455
Epoch 15/20
39000/60000 [==================>...........] - ETA: 0s - loss: 0.0842 - acc
```

```
: 0.9744 60000/60000 [==============================] - 2s 38us/step - loss:
0.0859 - acc: 0.9736 - val_loss: 0.1659 - val_acc: 0.9507
Epoch 16/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.0772
- acc: 0.9766 - val_loss: 0.1634 - val_acc: 0.9521
Epoch 17/20
60000/60000 [==============================] - 2s 38us/step - loss: 0.0689
- acc: 0.9791 - val_loss: 0.1392 - val_acc: 0.9559
Epoch 18/20
60000/60000 [==============================] - 2s 38us/step - loss: 0.0621
- acc: 0.9807 - val_loss: 0.1051 - val_acc: 0.9672
Epoch 19/20
60000/60000 [==============================] - 2s 38us/step - loss: 0.0566
- acc: 0.9826 - val_loss: 0.1138 - val_acc: 0.9647
Epoch 20/20
60000/60000 [==============================] - 2s 38us/step - loss: 0.0525
- acc: 0.9839 - val_loss: 0.0982 - val_acc: 0.9694
10000/10000 [==============================] - 1s 59us/step
Test score: 0.09823569706063717
Test Accuracy: 0.9694
```



In [44]:

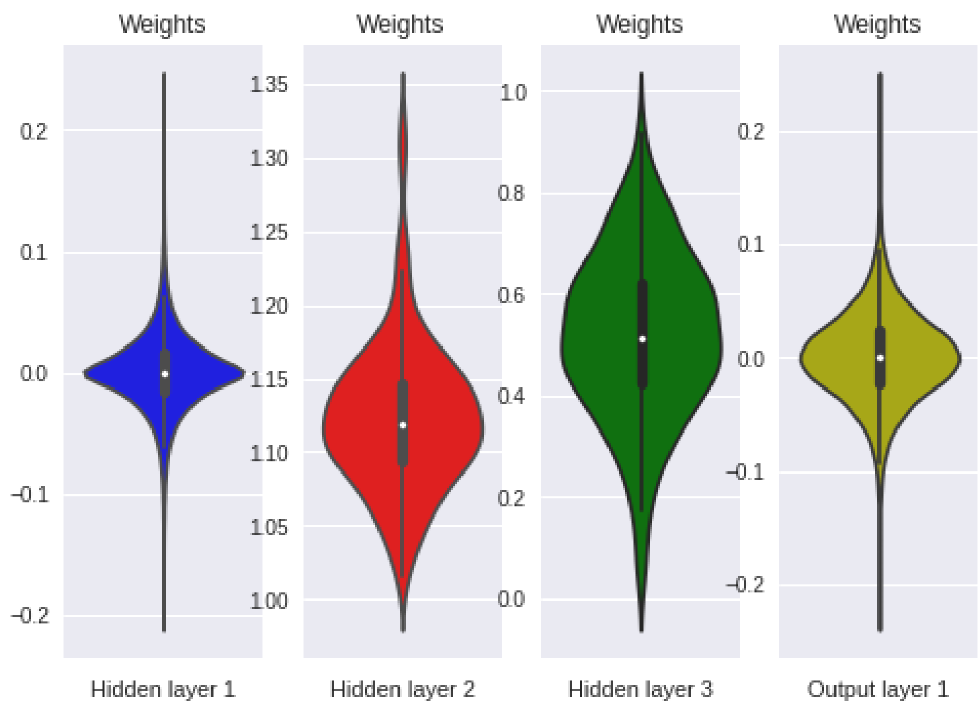
```
after_weights  = batch_model.get_weights()
h1_w = after_weights[0].flatten().reshape(-1,1)
h2_w = after_weights[2].flatten().reshape(-1,1)
h3_w = after_weights[4].flatten().reshape(-1,1)
out_w = after_weights[6].flatten().reshape(-1,1)
fig = mp.figure()
mp.subplot(1,4,1)
mp.title("Weights")
ax = s.violinplot(y  = h1_w, color='b')
mp.xlabel('Hidden layer 1')
mp.subplot(1,4,2)
mp.title("Weights")
ax = s.violinplot(y  = h2_w, color='r')
mp.xlabel('Hidden layer 2')
mp.subplot(1,4,3)
mp.title("Weights")
ax = s.violinplot(y  = h3_w, color='g')
```

```
ax = s.violinplot(y = h3_w, color='g')
mp.xlabel('Hidden layer 3')
mp.subplot(1,4,4)
mp.title("Weights")
ax = s.violinplot(y  = out_w, color='y')
mp.xlabel('Output layer 1')
```

```
/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)
```

Out[44]:

```
Text(0.5,0,'Output layer 1')
```




```
            MODEL 4: INPUT(784) - SIGMOID(160) - SIGMOID(80) -
SIGMOID(40) -
                              SIGMOID(20) - OUTPUT(SOFTMAX(10)) WITH
SGD OPTIMIZER + BATCH
                              NORMALIZATION ON HIDDEN LAYERS + DROP (
UT(0.5) ON HIDDEN LAYERS
```

In [47]:

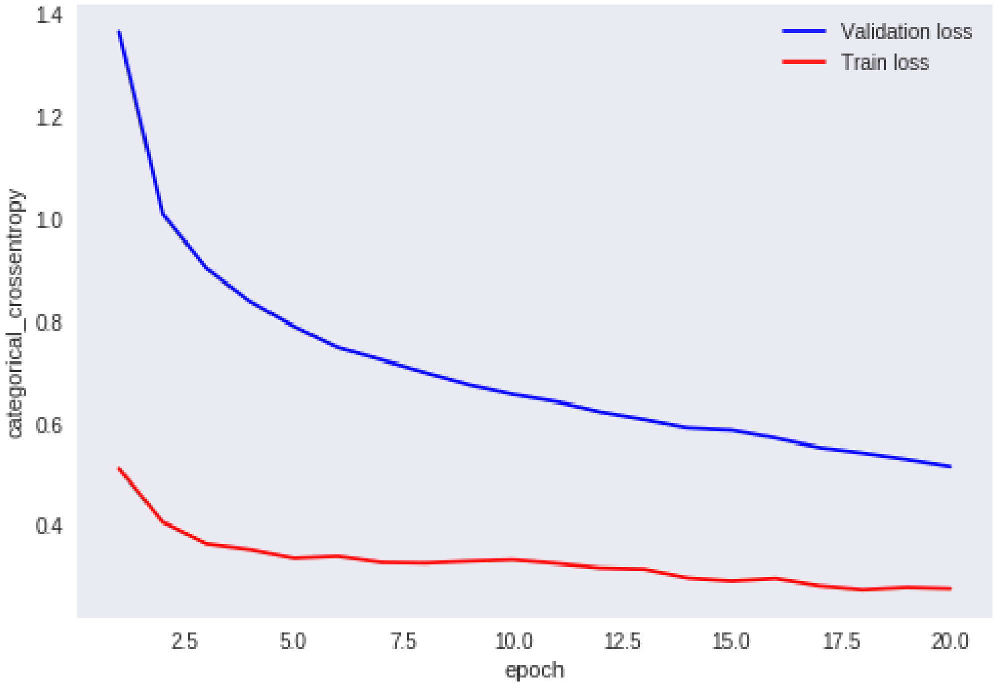
```
from keras.layers import Dropout
from keras.layers.normalization import BatchNormalization
drop_model = Sequential()
drop_model.add(Dense(160, activation = 'sigmoid', input_shape =
(input_shape,), kernel_initializer= RandomNormal(mean = 0, stddev= 0.00625,
seed= None)))
drop_model.add(BatchNormalization())
drop_model.add(Dropout(0.5))
drop_model.add(Dense(80, activation = 'sigmoid', kernel_initializer= Random
Normal(mean = 0, stddev= 0.0125, seed = None)))
```

```
Normal(mean = 0, stddev= 0.0125, seed = None)))
drop_model.add(BatchNormalization())
drop_model.add(Dropout(0.5))
drop_model.add(Dense(40, activation = 'sigmoid', kernel_initializer= Random
Normal(mean = 0, stddev= 0.025, seed = None)))
drop_model.add(BatchNormalization())
drop_model.add(Dropout(0.5))
drop_model.add(Dense(20, activation = 'sigmoid', kernel_initializer= Random
Normal(mean = 0, stddev= 0.05, seed = None)))
drop_model.add(BatchNormalization())
drop_model.add(Dropout(0.5))
drop_model.add(Dense(output_dim, activation  = 'softmax'))
drop_model.summary()
drop_model.compile(optimizer = 'adam', loss = 'categorical_crossentropy', m
etrics = ['accuracy'])
history = drop_model.fit(x_train, y_train, batch_size= batch_size, epochs=
number_of_epoch, validation_data=(x_test, y_test))
score = drop_model.evaluate(x_test, y_test)
print("Test score:", score[0])
print("Test Accuracy:", score[1])
fig,ax = mp.subplots(1,1)
ax.set_xlabel("epoch")
ax.set_ylabel("categorical_crossentropy")
x = list(range(1, number_of_epoch+1))
tl = history.history['loss']
vl = history.history['val_loss']
dynamic_plot(x,tl,vl,ax)
```

```
_________________________________________________________________
Layor (type)                 Output Shape              Param #
=================================================================
dense_52 (Dense)             (None, 160)               125600
_________________________________________________________________
batch_normalization_4 (Batch (None, 160)               640
_________________________________________________________________
dropout_1 (Dropout)          (None, 160)               0
_________________________________________________________________
dense_53 (Dense)             (None, 80)                12880
_________________________________________________________________
batch_normalization_5 (Batch (None, 80)                320
_________________________________________________________________
dropout_2 (Dropout)          (None, 80)                0
_________________________________________________________________
dense_54 (Dense)             (None, 40)                3240
_________________________________________________________________
batch_normalization_6 (Batch (None, 40)                160
_________________________________________________________________
dropout_3 (Dropout)          (None, 40)                0
_________________________________________________________________
dense_55 (Dense)             (None, 20)                820
_________________________________________________________________
batch_normalization_7 (Batch (None, 20)                80
_________________________________________________________________
dropout_4 (Dropout)          (None, 20)                0
_________________________________________________________________
dense_56 (Dense)             (None, 10)                210
=================================================================
Total params: 143,950
Trainable params: 143,350
Non-trainable params: 600
_________________________________________________________________
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 4s 68us/step - loss: 1.3655
- acc: 0.5419 - val_loss: 0.5116 - val_acc: 0.8638
Epoch 2/20
19000/60000 [========>.....................] - ETA: 1s - loss: 1.0586 - acc
: 0.663560000/60000 [==============================] - 3s 44us/step - loss:
1.0099 - acc: 0.6813 - val_loss: 0.4070 - val_acc: 0.8903
Epoch 3/20
60000/60000 [==============================] - 3s 44us/step - loss: 0.9032
- acc: 0.7149 - val_loss: 0.3644 - val_acc: 0.8959
Epoch 4/20
60000/60000 [==============================] - 3s 44us/step - loss: 0.8376
- acc: 0.7378 - val_loss: 0.3530 - val_acc: 0.8988
Epoch 5/20
60000/60000 [==============================] - 3s 45us/step - loss: 0.7896
- acc: 0.7554 - val_loss: 0.3362 - val_acc: 0.9028
Epoch 6/20
60000/60000 [==============================] - 3s 44us/step - loss: 0.7485
- acc: 0.7673 - val_loss: 0.3400 - val_acc: 0.8980
Epoch 7/20
60000/60000 [==============================] - 3s 44us/step - loss: 0.7243
- acc: 0.7767 - val_loss: 0.3280 - val_acc: 0.9018
Epoch 8/20
36000/60000 [=================>............] - ETA: 1s - loss: 0.7042 - acc
: 0.784860000/60000 [==============================] - 3s 44us/step - loss:
0.6993 - acc: 0.7867 - val_loss: 0.3267 - val_acc: 0.9044
Epoch 9/20
60000/60000 [==============================] - 3s 44us/step - loss: 0.6753
- acc: 0.7961 - val_loss: 0.3304 - val_acc: 0.9024
Epoch 10/20
60000/60000 [==============================] - 3s 44us/step - loss: 0.6567
- acc: 0.8040 - val_loss: 0.3332 - val_acc: 0.9008
Epoch 11/20
60000/60000 [==============================] - 3s 44us/step - loss: 0.6424
- acc: 0.8112 - val_loss: 0.3261 - val_acc: 0.9058
Epoch 12/20
60000/60000 [==============================] - 3s 43us/step - loss: 0.6224
- acc: 0.8165 - val_loss: 0.3173 - val_acc: 0.9056
Epoch 13/20
60000/60000 [==============================] - 3s 44us/step - loss: 0.6076
- acc: 0.8219 - val_loss: 0.3150 - val_acc: 0.9079
Epoch 14/20
37000/60000 [=================>............] - ETA: 0s - loss: 0.5975 - acc
: 0.828260000/60000 [==============================] - 3s 45us/step - loss:
0.5911 - acc: 0.8295 - val_loss: 0.2975 - val_acc: 0.9144
Epoch 15/20
60000/60000 [==============================] - 3s 44us/step - loss: 0.5868
- acc: 0.8317 - val_loss: 0.2917 - val_acc: 0.9155
Epoch 16/20
60000/60000 [==============================] - 3s 45us/step - loss: 0.5715
- acc: 0.8366 - val_loss: 0.2968 - val_acc: 0.9130
Epoch 17/20
60000/60000 [==============================] - 3s 45us/step - loss: 0.5528
- acc: 0.8439 - val_loss: 0.2824 - val_acc: 0.9167
Epoch 18/20
60000/60000 [==============================] - 3s 45us/step - loss: 0.5419
- acc: 0.8480 - val_loss: 0.2748 - val_acc: 0.9193
Epoch 19/20
60000/60000 [==============================] - 3s 45us/step - loss: 0.5294
```

```
- acc: 0.8530 - val_loss: 0.2794 - val_acc: 0.9198
Epoch 20/20
33000/60000 [===============>..............] - ETA: 1s - loss: 0.5187 - acc
: 0.857060000/60000 [==============================] - 3s 45us/step - loss:
0.5156 - acc: 0.8574 - val_loss: 0.2770 - val_acc: 0.9193
10000/10000 [==============================] - 1s 62us/step
Test score: 0.2770418862953782
Test Accuracy: 0.9193
```



In [48]:

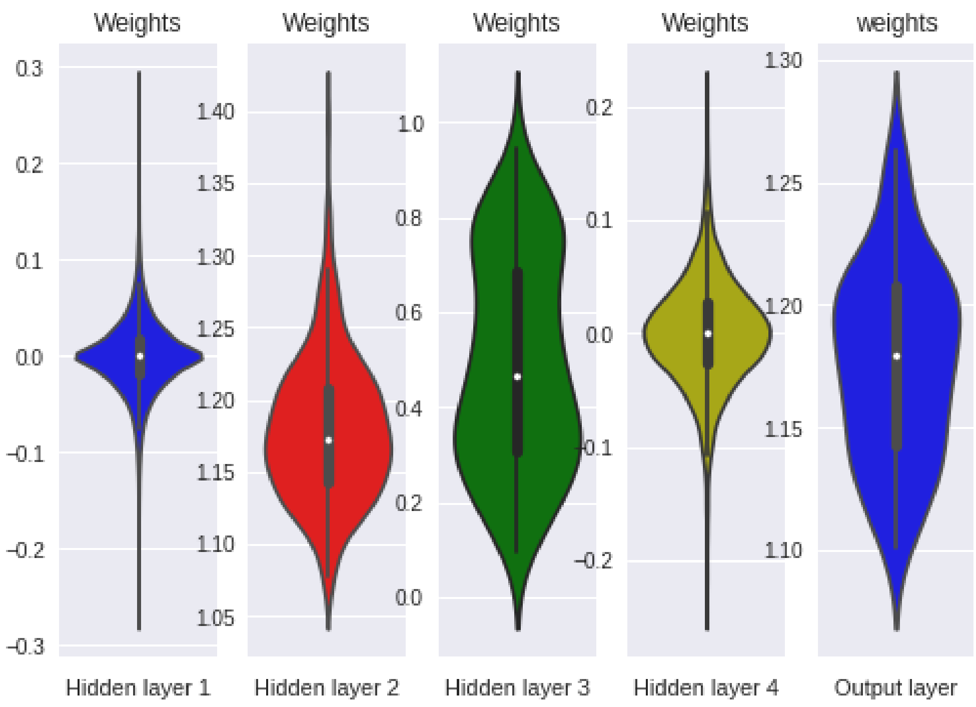
```
after_weights  = drop_model.get_weights()
h1_w = after_weights[0].flatten().reshape(-1,1)
h2_w = after_weights[2].flatten().reshape(-1,1)
h3_w = after_weights[4].flatten().reshape(-1,1)
h4_w = after_weights[6].flatten().reshape(-1,1)
out_w = after_weights[8].flatten().reshape(-1,1)
fig = mp.figure()
mp.subplot(1,5,1)
mp.title("Weights")
ax = s.violinplot(y  = h1_w, color='b')
mp.xlabel('Hidden layer 1')
mp.subplot(1,5,2)
mp.title("Weights")
ax = s.violinplot(y  = h2_w, color='r')
mp.xlabel('Hidden layer 2')
mp.subplot(1,5,3)
mp.title("Weights")
ax = s.violinplot(y  = h3_w, color='g')
mp.xlabel('Hidden layer 3')
mp.subplot(1,5,4)
mp.title("Weights")
ax = s.violinplot(y  = h4_w, color='y')
mp.xlabel('Hidden layer 4')
mp.subplot(1,5,5)
mp.title('weights')
ax = s.violinplot(y = out_w, color = 'b')
mp.xlabel('Output layer')
```

```
/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)
```

Out[48]:

```
Text(0.5,0,'Output layer')
```



HYPER PARAMETER TUNING FOR KERAS USING SCIKIT-LEARN

In [0]:

```
from keras.optimizers import adagrad, rmsprop, sgd, adadelta, adam
def hyperparameter_tune(activ):
  model = Sequential()
  model.add(Dense(640, activation=activ, input_shape = (input_shape,)))
  model.add(Dense(320, activation = activ))
  model.add(Dense(80, activation  = activ))
  model.add(Dense(10, activation = 'softmax'))

  model.compile(loss = 'categorical_crossentropy', optimizer = 'sgd', metri
cs = ['accuracy'])
  return model
```

In [57]:

```
from keras.wrappers.scikit_learn import KerasClassifier
from sklearn.model_selection import GridSearchCV
activ = ['sigmoid', 'relu']
model = KerasClassifier(build_fn = hyperparameter_tune, epochs =
number_of_epoch, batch_size = batch_size)
param_grid = dict(activ = activ)
grid = GridSearchCV(estimator = model, param_grid = param_grid)
grid_result = grid.fit(x_train, y_train)
```

```
Epoch 1/20
```

```
Epoch 1/20
40000/40000 [==============================] - 4s 88us/step - loss: 2.3534
- acc: 0.0987
Epoch 2/20
40000/40000 [==============================] - 3s 78us/step - loss: 2.3034
- acc: 0.1174
Epoch 3/20
40000/40000 [==============================] - 3s 76us/step - loss: 2.3003
- acc: 0.1115
Epoch 4/20
40000/40000 [==============================] - 3s 78us/step - loss: 2.2995
- acc: 0.1115
Epoch 5/20
40000/40000 [==============================] - 3s 78us/step - loss: 2.2989
- acc: 0.1115
Epoch 6/20
40000/40000 [==============================] - 3s 79us/step - loss: 2.2983
- acc: 0.1115
Epoch 7/20
22000/40000 [===============>..............] - ETA: 1s - loss: 2.2979 - acc
: 0.110340000/40000 [==============================] - 3s 79us/step - loss:
2.2977 - acc: 0.1115
Epoch 8/20
40000/40000 [==============================] - 3s 78us/step - loss: 2.2971
- acc: 0.1115
Epoch 9/20
40000/40000 [==============================] - 3s 79us/step - loss: 2.2965
- acc: 0.1115
Epoch 10/20
40000/40000 [==============================] - 3s 77us/step - loss: 2.2959
- acc: 0.1115
Epoch 11/20
40000/40000 [==============================] - 3s 78us/step - loss: 2.2953
- acc: 0.1115
Epoch 12/20
40000/40000 [==============================] - 3s 78us/step - loss: 2.2947
- acc: 0.1115
Epoch 13/20
28000/40000 [====================>.........] - ETA: 0s - loss: 2.2942 - acc
: 0.111240000/40000 [==============================] - 3s 79us/step - loss:
2.2940 - acc: 0.1115
Epoch 14/20
40000/40000 [==============================] - 3s 77us/step - loss: 2.2935
- acc: 0.1115
Epoch 15/20
40000/40000 [==============================] - 3s 75us/step - loss: 2.2928
- acc: 0.1115
Epoch 16/20
40000/40000 [==============================] - 3s 77us/step - loss: 2.2922
- acc: 0.1115
Epoch 17/20
40000/40000 [==============================] - 3s 77us/step - loss: 2.2916
- acc: 0.1115
Epoch 18/20
40000/40000 [==============================] - 3s 77us/step - loss: 2.2909
- acc: 0.1115
Epoch 19/20
28000/40000 [====================>.........] - ETA: 0s - loss: 2.2902 - acc
: 0.112640000/40000 [==============================] - 3s 78us/step - loss:
2.2903 - acc: 0.1115
Epoch 20/20
```

```
Epoch 20/20
40000/40000 [==============================] - 3s 78us/step - loss: 2.2896
- acc: 0.1115
20000/20000 [==============================] - 1s 46us/step
40000/40000 [==============================] - 1s 33us/step
Epoch 1/20
40000/40000 [==============================] - 4s 91us/step - loss: 2.4100
- acc: 0.0804
Epoch 2/20
40000/40000 [==============================] - 3s 77us/step - loss: 2.3120
- acc: 0.0912
Epoch 3/20
40000/40000 [==============================] - 3s 78us/step - loss: 2.3021
- acc: 0.0973
Epoch 4/20
28000/40000 [====================>.........] - ETA: 0s - loss: 2.3008 - acc
: 0.111440000/40000 [==============================] - 3s 77us/step - loss:
2.3007 - acc: 0.1115
Epoch 5/20
40000/40000 [==============================] - 3s 78us/step - loss: 2.3001
- acc: 0.1115
Epoch 6/20
40000/40000 [==============================] - 3s 78us/step - loss: 2.2996
- acc: 0.1115
Epoch 7/20
40000/40000 [==============================] - 3s 78us/step - loss: 2.2990
- acc: 0.1115
Epoch 8/20
40000/40000 [==============================] - 3s 78us/step - loss: 2.2985
- acc: 0.1117
Epoch 9/20
40000/40000 [==============================] - 3s 77us/step - loss: 2.2980
- acc: 0.1115
Epoch 10/20
29000/40000 [====================>.........] - ETA: 0s - loss: 2.2977 - acc
: 0.110640000/40000 [==============================] - 3s 78us/step - loss:
2.2975 - acc: 0.1115
Epoch 11/20
40000/40000 [==============================] - 3s 78us/step - loss: 2.2970
- acc: 0.1115
Epoch 12/20
40000/40000 [==============================] - 3s 76us/step - loss: 2.2965
- acc: 0.1115
Epoch 13/20
40000/40000 [==============================] - 3s 77us/step - loss: 2.2960
- acc: 0.1115
Epoch 14/20
40000/40000 [==============================] - 3s 76us/step - loss: 2.2955
- acc: 0.1116
Epoch 15/20
40000/40000 [==============================] - 3s 77us/step - loss: 2.2950
- acc: 0.1115
Epoch 16/20
28000/40000 [====================>.........] - ETA: 0s - loss: 2.2943 - acc
: 0.112840000/40000 [==============================] - 3s 76us/step - loss:
2.2944 - acc: 0.1115
Epoch 17/20
40000/40000 [==============================] - 3s 77us/step - loss: 2.2939
- acc: 0.1117
Epoch 18/20
40000/40000 [==============================] - 3s 77us/step - loss: 2.2934
```

```
- acc: 0.1115
Epoch 19/20
40000/40000 [==============================] - 3s 77us/step - loss: 2.2929
- acc: 0.1118
Epoch 20/20
40000/40000 [==============================] - 3s 77us/step - loss: 2.2923
- acc: 0.1115
20000/20000 [==============================] - 1s 44us/step
40000/40000 [==============================] - 1s 33us/step
Epoch 1/20
34000/40000 [========================>.....] - ETA: 0s - loss: 2.3532 - acc
: 0.112240000/40000 [==============================] - 4s 93us/step - loss:
2.3473 - acc: 0.1130
Epoch 2/20
40000/40000 [==============================] - 3s 78us/step - loss: 2.3039
- acc: 0.1141
Epoch 3/20
40000/40000 [==============================] - 3s 78us/step - loss: 2.2988
- acc: 0.1141
Epoch 4/20
40000/40000 [==============================] - 3s 78us/step - loss: 2.2978
- acc: 0.1141
Epoch 5/20
40000/40000 [==============================] - 3s 78us/step - loss: 2.2972
- acc: 0.1141
Epoch 6/20
40000/40000 [==============================] - 3s 77us/step - loss: 2.2966
- acc: 0.1141
Epoch 7/20
30000/40000 [=====================>........] - ETA: 0s - loss: 2.2962 - acc
: 0.113840000/40000 [==============================] - 3s 76us/step - loss:
2.2960 - acc: 0.1141
Epoch 8/20
40000/40000 [==============================] - 3s 74us/step - loss: 2.2954
- acc: 0.1141
Epoch 9/20
40000/40000 [==============================] - 3s 77us/step - loss: 2.2948
- acc: 0.1141
Epoch 10/20
40000/40000 [==============================] - 3s 76us/step - loss: 2.2942
- acc: 0.1141
Epoch 11/20
40000/40000 [==============================] - 3s 77us/step - loss: 2.2936
- acc: 0.1141
Epoch 12/20
40000/40000 [==============================] - 3s 78us/step - loss: 2.2930
- acc: 0.1141
Epoch 13/20
29000/40000 [====================>.........] - ETA: 0s - loss: 2.2928 - acc
: 0.112240000/40000 [==============================] - 3s 77us/step - loss:
2.2924 - acc: 0.1141
Epoch 14/20
40000/40000 [==============================] - 3s 77us/step - loss: 2.2918
- acc: 0.1141
Epoch 15/20
40000/40000 [==============================] - 3s 76us/step - loss: 2.2911
- acc: 0.1141
Epoch 16/20
40000/40000 [==============================] - 3s 76us/step - loss: 2.2905
- acc: 0.1141
```

```
Epoch 17/20
40000/40000 [==============================] - 3s 77us/step - loss: 2.2899
- acc: 0.1141
Epoch 18/20
40000/40000 [==============================] - 3s 77us/step - loss: 2.2893
- acc: 0.1141
Epoch 19/20
28000/40000 [====================>.........] - ETA: 0s - loss: 2.2890 - acc
: 0.113540000/40000 [==============================] - 3s 76us/step - loss:
2.2886 - acc: 0.1141
Epoch 20/20
40000/40000 [==============================] - 3s 76us/step - loss: 2.2880
- acc: 0.1141
20000/20000 [==============================] - 1s 43us/step
40000/40000 [==============================] - 1s 32us/step
Epoch 1/20
40000/40000 [==============================] - 4s 96us/step - loss: 2.1997
- acc: 0.2195
Epoch 2/20
40000/40000 [==============================] - 3s 76us/step - loss: 1.9482
- acc: 0.5110
Epoch 3/20
40000/40000 [==============================] - 3s 77us/step - loss: 1.6651
- acc: 0.6676
Epoch 4/20
27000/40000 [===================>..........] - ETA: 1s - loss: 1.4148 - acc
: 0.739340000/40000 [==============================] - 3s 78us/step - loss:
1.3664 - acc: 0.7502
Epoch 5/20
40000/40000 [==============================] - 3s 78us/step - loss: 1.1043
- acc: 0.7968
Epoch 6/20
40000/40000 [==============================] - 3s 78us/step - loss: 0.9096
- acc: 0.8215
Epoch 7/20
40000/40000 [==============================] - 3s 78us/step - loss: 0.7747
- acc: 0.8374
Epoch 8/20
40000/40000 [==============================] - 3s 77us/step - loss: 0.6802
- acc: 0.8490
Epoch 9/20
40000/40000 [==============================] - 3s 78us/step - loss: 0.6119
- acc: 0.8570
Epoch 10/20
29000/40000 [====================>.........] - ETA: 0s - loss: 0.5672 - acc
: 0.863840000/40000 [==============================] - 3s 79us/step - loss:
0.5610 - acc: 0.8645
Epoch 11/20
40000/40000 [==============================] - 3s 80us/step - loss: 0.5214
- acc: 0.8711
Epoch 12/20
40000/40000 [==============================] - 3s 79us/step - loss: 0.4898
- acc: 0.8769
Epoch 13/20
40000/40000 [==============================] - 3s 78us/step - loss: 0.4640
- acc: 0.8806
Epoch 14/20
40000/40000 [==============================] - 3s 79us/step - loss: 0.4426
- acc: 0.8851
Epoch 15/20
```

```
40000/40000 [==============================] - 3s 79us/step - loss: 0.4245
- acc: 0.8883
Epoch 16/20
28000/40000 [====================>.........] - ETA: 0s - loss: 0.4144 - acc
: 0.890040000/40000 [==============================] - 3s 78us/step - loss:
0.4090 - acc: 0.8919
Epoch 17/20
40000/40000 [==============================] - 3s 79us/step - loss: 0.3956
- acc: 0.8947
Epoch 18/20
40000/40000 [==============================] - 3s 78us/step - loss: 0.3837
- acc: 0.8974
Epoch 19/20
40000/40000 [==============================] - 3s 78us/step - loss: 0.3734
- acc: 0.8990
Epoch 20/20
40000/40000 [==============================] - 3s 78us/step - loss: 0.3641
- acc: 0.9012
20000/20000 [==============================] - 1s 44us/step
40000/40000 [==============================] - 1s 33us/step
Epoch 1/20
34000/40000 [========================>.....] - ETA: 0s - loss: 2.2243 - acc
: 0.167140000/40000 [==============================] - 4s 92us/step - loss:
2.2065 - acc: 0.1884
Epoch 2/20
40000/40000 [==============================] - 3s 76us/step - loss: 1.9649
- acc: 0.5095
Epoch 3/20
40000/40000 [==============================] - 3s 76us/step - loss: 1.6852
- acc: 0.6830
Epoch 4/20
40000/40000 [==============================] - 3s 78us/step - loss: 1.3794
- acc: 0.7558
Epoch 5/20
40000/40000 [==============================] - 3s 76us/step - loss: 1.1024
- acc: 0.7954
Epoch 6/20
40000/40000 [==============================] - 3s 77us/step - loss: 0.8972
- acc: 0.8205
Epoch 7/20
30000/40000 [=====================>........] - ETA: 0s - loss: 0.7686 - acc
: 0.837240000/40000 [==============================] - 3s 76us/step - loss:
0.7567 - acc: 0.8372
Epoch 8/20
40000/40000 [==============================] - 3s 77us/step - loss: 0.6609
- acc: 0.8490
Epoch 9/20
40000/40000 [==============================] - 3s 78us/step - loss: 0.5932
- acc: 0.8579
Epoch 10/20
40000/40000 [==============================] - 3s 80us/step - loss: 0.5434
- acc: 0.8656
Epoch 11/20
40000/40000 [==============================] - 3s 79us/step - loss: 0.5054
- acc: 0.8719
Epoch 12/20
40000/40000 [==============================] - 3s 80us/step - loss: 0.4756
- acc: 0.8765
Epoch 13/20
29000/40000 [====================>.........] - ETA: 0s - loss: 0.4586 - acc
```

```
: 0.879340000/40000 [==============================] - 3s 80us/step - loss:
0.4515 - acc: 0.8812
Epoch 14/20
40000/40000 [==============================] - 3s 80us/step - loss: 0.4314
- acc: 0.8853
Epoch 15/20
40000/40000 [==============================] - 3s 78us/step - loss: 0.4144
- acc: 0.8886
Epoch 16/20
40000/40000 [==============================] - 3s 78us/step - loss: 0.3999
- acc: 0.8913
Epoch 17/20
40000/40000 [==============================] - 3s 79us/step - loss: 0.3874
- acc: 0.8942
Epoch 18/20
40000/40000 [==============================] - 3s 79us/step - loss: 0.3763
- acc: 0.8967
Epoch 19/20
28000/40000 [====================>.........] - ETA: 0s - loss: 0.3696 - acc
: 0.898040000/40000 [==============================] - 3s 78us/step - loss:
0.3665 - acc: 0.8993
Epoch 20/20
40000/40000 [==============================] - 3s 77us/step - loss: 0.3576
- acc: 0.9012
20000/20000 [==============================] - 1s 44us/step
40000/40000 [==============================] - 1s 32us/step
Epoch 1/20
40000/40000 [==============================] - 4s 96us/step - loss: 2.2087
- acc: 0.3134
Epoch 2/20
40000/40000 [==============================] - 3s 75us/step - loss: 1.9840
- acc: 0.5594
Epoch 3/20
40000/40000 [==============================] - 3s 75us/step - loss: 1.7116
- acc: 0.6780
Epoch 4/20
28000/40000 [====================>.........] - ETA: 0s - loss: 1.4585 - acc
: 0.742540000/40000 [==============================] - 3s 77us/step - loss:
1.4141 - acc: 0.7510
Epoch 5/20
40000/40000 [==============================] - 3s 77us/step - loss: 1.1410
- acc: 0.7918
Epoch 6/20
40000/40000 [==============================] - 3s 77us/step - loss: 0.9316
- acc: 0.8131
Epoch 7/20
40000/40000 [==============================] - 3s 76us/step - loss: 0.7862
- acc: 0.8299
Epoch 8/20
40000/40000 [==============================] - 3s 75us/step - loss: 0.6862
- acc: 0.8424
Epoch 9/20
40000/40000 [==============================] - 3s 76us/step - loss: 0.6153
- acc: 0.8533
Epoch 10/20
29000/40000 [====================>.........] - ETA: 0s - loss: 0.5647 - acc
: 0.861040000/40000 [==============================] - 3s 77us/step - loss:
0.5629 - acc: 0.8604
Epoch 11/20
40000/40000 [==============================] - 3s 76us/step - loss: 0.5226
```

```
- acc: 0.8691
Epoch 12/20
40000/40000 [==============================] - 3s 77us/step - loss: 0.4910
- acc: 0.8743
Epoch 13/20
40000/40000 [==============================] - 3s 85us/step - loss: 0.4651
- acc: 0.8796
Epoch 14/20
40000/40000 [==============================] - 3s 77us/step - loss: 0.4436
- acc: 0.8838
Epoch 15/20
40000/40000 [==============================] - 3s 79us/step - loss: 0.4256
- acc: 0.8876
Epoch 16/20
28000/40000 [====================>.........] - ETA: 0s - loss: 0.4144 - acc
: 0.889240000/40000 [==============================] - 3s 79us/step - loss:
0.4101 - acc: 0.8904
Epoch 17/20
40000/40000 [==============================] - 3s 78us/step - loss: 0.3967
- acc: 0.8928
Epoch 18/20
40000/40000 [==============================] - 3s 77us/step - loss: 0.3851
- acc: 0.8953
Epoch 19/20
40000/40000 [==============================] - 3s 78us/step - loss: 0.3746
- acc: 0.8976
Epoch 20/20
40000/40000 [==============================] - 3s 79us/step - loss: 0.3653
- acc: 0.9001
20000/20000 [==============================] - 1s 47us/step
40000/40000 [==============================] - 1s 33us/step
Epoch 1/20
32000/60000 [===============>..............] - ETA: 2s - loss: 2.2277 - acc
: 0.198560000/60000 [==============================] - 5s 90us/step - loss:
2.1401 - acc: 0.3058
Epoch 2/20
60000/60000 [==============================] - 5s 78us/step - loss: 1.7291
- acc: 0.6136
Epoch 3/20
60000/60000 [==============================] - 5s 78us/step - loss: 1.2835
- acc: 0.7470
Epoch 4/20
60000/60000 [==============================] - 5s 78us/step - loss: 0.9437
- acc: 0.8027
Epoch 5/20
60000/60000 [==============================] - 5s 78us/step - loss: 0.7407
- acc: 0.8349
Epoch 6/20
27000/60000 [============>.................] - ETA: 2s - loss: 0.6418 - acc
: 0.851860000/60000 [==============================] - 5s 77us/step - loss:
0.6196 - acc: 0.8546
Epoch 7/20
60000/60000 [==============================] - 5s 79us/step - loss: 0.5426
- acc: 0.8668
Epoch 8/20
60000/60000 [==============================] - 5s 78us/step - loss: 0.4908
- acc: 0.8766
Epoch 9/20
60000/60000 [==============================] - 5s 78us/step - loss: 0.4535
- acc: 0.8837
Epoch 10/20
```

```
Epoch 10/20
60000/60000 [==============================] - 5s 78us/step - loss: 0.4255
- acc: 0.8889
Epoch 11/20
26000/60000 [============>.................] - ETA: 2s - loss: 0.4115 - acc
: 0.890060000/60000 [==============================] - 5s 78us/step - loss:
0.4039 - acc: 0.8926
Epoch 12/20
60000/60000 [==============================] - 5s 79us/step - loss: 0.3863
- acc: 0.8961
Epoch 13/20
60000/60000 [==============================] - 5s 78us/step - loss: 0.3719
- acc: 0.8989
Epoch 14/20
60000/60000 [==============================] - 5s 77us/step - loss: 0.3597
- acc: 0.9013
Epoch 15/20
60000/60000 [==============================] - 5s 78us/step - loss: 0.3492
- acc: 0.9040
Epoch 16/20
25000/60000 [===========>..................] - ETA: 2s - loss: 0.3470 - acc
: 0.904160000/60000 [==============================] - 5s 78us/step - loss:
0.3398 - acc: 0.9059
Epoch 17/20
60000/60000 [==============================] - 5s 77us/step - loss: 0.3316
- acc: 0.9080
Epoch 18/20
60000/60000 [==============================] - 5s 77us/step - loss: 0.3242
- acc: 0.9093
Epoch 19/20
60000/60000 [==============================] - 5s 78us/step - loss: 0.3174
- acc: 0.9115
Epoch 20/20
60000/60000 [==============================] - 5s 78us/step - loss: 0.3112
- acc: 0.9127
```

In [59]:

```python
print("Best %f using %s is:" %(grid_result.best_score_,
grid_result.best_params_))
mean = grid_result.cv_results_['mean_test_score']
stdv = grid_result.cv_results_['std_test_score']
params = grid_result.cv_results_['params']
for mean, stdv, params in zip(mean, stdv, params):
  print("%f %f with %r" %(mean,stdv,params))
```

```
Best 0.898233 using {'activ': 'relu'} is:
0.112367 0.002416 with {'activ': 'sigmoid'}
0.898233 0.002429 with {'activ': 'relu'}
```

```
            CONCLUSION:

                  MODEL 1 : INPUT(784) - SIGMOID(640) - SIGMOID(320) - S
   IGMOID(120) - OUTPUT(SOFTMAXT(10))

                              SGD : TRAIN LOSS: 2.2851 VALIDATION LOSS: 2
   .2840 ACCURACY: 11.42
```

ADAM: TRAIN LOSS : 0.0481 VALIDATION LOSS: 0.0832 ACCURACY : 97.39

MODEL 2 : INPUT(784) - RELU(400) - RELU(300) - RELU(20) - RELU(100) - RELU(50) - OUTPUT(SOFTMAX(10))

SGD: TRAIN LOSS: 0.3036 VALIDATION LOSS: 0.9145 ACCURACY: 91.72

ADAM: TRAIN LOSS: 0.0040 VALIDATION LOSS: 0.0863 ACCURACY: 98.04

MODEL 3 : INPUT(784) - SIGMOID(160) - SIGMOID(80) - SIGMOID(40) - OUTPUT(SOFTMAX(10))

BATCH NORMALIZATION IS APPLIED ON ALL HIDDEN LAYERS USING UNIFORM INITIALIZATION OF WEIGHTS

ADAM: TRAIN LOSS: 0.0525 VALIDATION LOSS: 0.0982 ACCURACY: 96.94

MODEL 4 : INPUT(784) - SIGMOID(160) - SIGMOID(80) - SIGMOID(40) - SIGMOID(20) - OUTPUT(SPFTMAX(10))

BATCH NORMALIZATION AND DROP OUT(0.5)

ADAM : TRAIN LOSS: 0.5187 VALIDATION LOSS: 0.277 ACCURACY: 91.93

HYPER PARAMETERS TUNING:

BEST ACTIVE FUNCTION : RELU