Keras -- MLPs on MNIST

In [1]:

```
# if you keras is not using tensorflow as backend set "KERAS_BACKEND=tensorflow" use this command
from keras.utils import np_utils
from keras.datasets import mnist
import seaborn as sns
from keras.initializers import RandomNormal
```

```
Using TensorFlow backend.
```

In [2]:

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

In [3]:

```
# the data, shuffled and split between train and test sets
(X_train, y_train), (X_test, y_test) = mnist.load_data()
```

In [4]:

```
print("Number of training examples :", X_train.shape[0], "and each image is of shape (%d, %d)"%(X_
train.shape[1], X_train.shape[2]))
print("Number of training examples :", X_test.shape[0], "and each image is of shape (%d,
%d)"%(X_test.shape[1], X_test.shape[2]))
```

```
Number of training examples : 60000 and each image is of shape (28, 28)
Number of training examples : 10000 and each image is of shape (28, 28)
```

In [5]:

```
# if you observe the input shape its 2 dimensional vector
# for each image we have a (28*28) vector
# we will convert the (28*28) vector into single dimensional vector of 1 * 784

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])
```

In [6]:

```
# after converting the input images from 3d to 2d vectors

print("Number of training examples :", X_train.shape[0], "and each image is of shape
(%d)"%(X_train.shape[1]))
print("Number of training examples :", X_test.shape[0], "and each image is of shape (%d)"%(X_test.
shape[1]))
```

```
Number of training examples : 60000 and each image is of shape (784)
Number of training examples : 10000 and each image is of shape (784)
```

In [7]:

```
# An example data point
print(X_train[0])
```

```
[   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   3  18  18  18 126 136 175  26 166 255
  247 127   0   0   0   0   0   0   0   0   0   0   0   0  30  36  94 154
  170 253 253 253 253 253 225 172 253 242 195  64   0   0   0   0   0   0
    0   0   0   0   0  49 238 253 253 253 253 253 253 253 253 251  93  82
   82  56  39   0   0   0   0   0   0   0   0   0   0   0   0  18 219 253
  253 253 253 253 198 182 247 241   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0  80 156 107 253 253 205  11   0  43 154
    0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0  14   1 154 253  90   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0   0   0   0 139 253 190   2   0
    0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0  11 190 253  70   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0  35 241
  225 160 108   1   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0  81 240 253 253 119  25   0   0   0
    0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0  45 186 253 253 150  27   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0   0   0   0  16  93 252 253 187
    0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0 249 253 249  64   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0   0   0   0   0  46 130 183 253
  253 207   2   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0  39 148 229 253 253 253 250 182   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0   0   0  24 114 221 253 253 253
  253 201  78   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0  23  66 213 253 253 253 253 198  81   2   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0  18 171 219 253 253 253 253 195
   80   9   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
   55 172 226 253 253 253 253 244 133  11   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0 136 253 253 253 212 135 132  16
    0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   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]:

```
# if we observe the above matrix each cell is having a value between 0-255
# before we move to apply machine learning algorithms lets try to normalize the data
# X => (X - Xmin)/(Xmax-Xmin) = X/255

X_train = X_train/255
X_test = X_test/255
```

In [9]:

```
# example data point after normlizing
print(X_train[0])
```

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

```
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.01176471 0.07058824 0.07058824 0.07058824
0.49411765 0.53333333 0.68627451 0.10196078 0.65098039 1.
0.96862745 0.49803922 0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.11764706 0.14117647 0.36862745 0.60392157
0.66666667 0.99215686 0.99215686 0.99215686 0.99215686 0.99215686
0.88235294 0.6745098  0.99215686 0.94901961 0.76470588 0.25098039
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.19215686
0.93333333 0.99215686 0.99215686 0.99215686 0.99215686 0.99215686
0.99215686 0.99215686 0.99215686 0.98431373 0.36470588 0.32156863
0.32156863 0.21960784 0.15294118 0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.07058824 0.85882353 0.99215686
0.99215686 0.99215686 0.99215686 0.99215686 0.77647059 0.71372549
0.96862745 0.94509804 0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.31372549 0.61176471 0.41960784 0.99215686
0.99215686 0.80392157 0.04313725 0.         0.16862745 0.60392157
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.05490196 0.00392157 0.60392157 0.99215686 0.35294118
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.54509804 0.99215686 0.74509804 0.00784314 0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.04313725
0.74509804 0.99215686 0.2745098  0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.1372549  0.94509804
0.88235294 0.62745098 0.42352941 0.00392157 0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.31764706 0.94117647 0.99215686
0.99215686 0.46666667 0.09803922 0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.17647059 0.72941176 0.99215686 0.99215686
0.58823529 0.10588235 0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.0627451  0.36470588 0.98823529 0.99215686 0.73333333
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.97647059 0.99215686 0.97647059 0.25098039 0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.18039216 0.50980392 0.71764706 0.99215686
```

```
 0.99215686 0.81176471 0.00784314 0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.15294118 0.58039216
 0.89803922 0.99215686 0.99215686 0.99215686 0.98039216 0.71372549
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.09411765 0.44705882 0.86666667 0.99215686 0.99215686 0.99215686
 0.99215686 0.78823529 0.30588235 0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.09019608 0.25882353 0.83529412 0.99215686
 0.99215686 0.99215686 0.99215686 0.77647059 0.31764706 0.00784314
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.07058824 0.67058824
 0.85882353 0.99215686 0.99215686 0.99215686 0.99215686 0.76470588
 0.31372549 0.03529412 0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.21568627 0.6745098  0.88627451 0.99215686 0.99215686 0.99215686
 0.99215686 0.95686275 0.52156863 0.04313725 0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.53333333 0.99215686
 0.99215686 0.99215686 0.83137255 0.52941176 0.51764706 0.0627451
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         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 [10]:

```python
# here we are having a class number for each image
print("Class label of first image :", y_train[0])

# lets convert this into a 10 dimensional vector
# ex: consider an image is 5 convert it into 5 => [0, 0, 0, 0, 0, 1, 0, 0, 0, 0]
# this conversion needed for MLPs

Y_train = np_utils.to_categorical(y_train, 10)
Y_test = np_utils.to_categorical(y_test, 10)

print("After converting the output into a vector : ",Y_train[0])
```

```
Class label of first image : 5
After converting the output into a vector :  [0. 0. 0. 0. 0. 1. 0. 0. 0. 0.]
```

Softmax classifier

In [11]:

```python
#importing

from keras.models import Sequential
from keras.layers import Dense, Activation
from keras.layers.normalization import BatchNormalization
from keras.layers import Dropout
from prettytable import PrettyTable
```

In [12]:

```
# some model parameters

output_dim = 10
input_dim = X_train.shape[1]

batch_size = 128
nb_epoch = 20
```

1.1)MLP with 2 hidden layers + Relu + BatchNormalisation +Dropout+ AdamOpltimizer

In [14]:

```
model_relu = Sequential()
#Let's take dimension of first and second hidden layer 400 and 250 respectively
# If we sample weights from a normal distribution N(0,σ) we satisfy this condition with
σ=√(2/(ni).
# h1 =>  σ=√(2/(fan_in) = 0.070  => N(0,σ) = N(0,0.070)
# h2 =>  σ=√(2/(fan_in) = 0.089  => N(0,σ) = N(0,0.089)

model_relu.add(Dense(400, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNor
mal(mean=0.0, stddev=0.070, seed=None)))
model_relu.add(BatchNormalization())
model_relu.add(Dropout(0.5))
model_relu.add(Dense(250, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.089
, seed=None)) )
model_relu.add(BatchNormalization())
model_relu.add(Dropout(0.5))
model_relu.add(Dense(output_dim, activation='softmax'))

model_relu.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_4 (Dense)              (None, 400)               314000    
_________________________________________________________________
batch_normalization_3 (Batch (None, 400)               1600      
_________________________________________________________________
dropout_3 (Dropout)          (None, 400)               0         
_________________________________________________________________
dense_5 (Dense)              (None, 250)               100250    
_________________________________________________________________
batch_normalization_4 (Batch (None, 250)               1000      
_________________________________________________________________
dropout_4 (Dropout)          (None, 250)               0         
_________________________________________________________________
dense_6 (Dense)              (None, 10)                2510      
=================================================================
Total params: 419,360
Trainable params: 418,060
Non-trainable params: 1,300
_________________________________________________________________
```

In [15]:

```
#Applying adam optimizer
model_relu.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history = model_relu.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, valid
ation_data=(X_test, Y_test))
```

```
W0804 15:39:09.342900  6892 deprecation_wrapper.py:119] From C:\Users\Hi\Anaconda3\lib\site-
packages\keras\optimizers.py:790: The name tf.train.Optimizer is deprecated. Please use
tf.compat.v1.train.Optimizer instead.

W0804 15:39:10.184588  6892 deprecation.py:323] From C:\Users\Hi\Anaconda3\lib\site-
packages\tensorflow\python\ops\math_grad.py:1250: add_dispatch_support.<locals>.wrapper (from
tensorflow.python.ops.array_ops) is deprecated and will be removed in a future version.
```

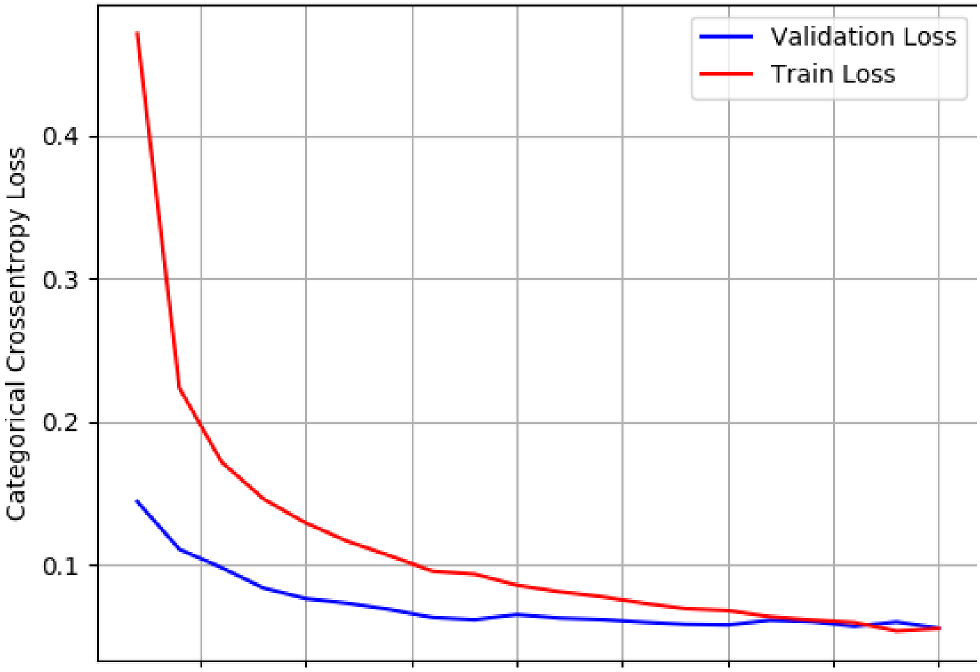
```
Instructions for updating:
Use tf.where in 2.0, which has the same broadcast rule as np.where

Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 34s 572us/step - loss: 0.4713 - acc: 0.8576 - val_l
oss: 0.1440 - val_acc: 0.9551
Epoch 2/20
60000/60000 [==============================] - 26s 427us/step - loss: 0.2234 - acc: 0.9323 - val_l
oss: 0.1106 - val_acc: 0.9661
Epoch 3/20
60000/60000 [==============================] - 26s 430us/step - loss: 0.1717 - acc: 0.9467 - val_l
oss: 0.0978 - val_acc: 0.9700
Epoch 4/20
60000/60000 [==============================] - 25s 424us/step - loss: 0.1457 - acc: 0.9557 - val_l
oss: 0.0834 - val_acc: 0.9739
Epoch 5/20
60000/60000 [==============================] - 25s 424us/step - loss: 0.1289 - acc: 0.9608 - val_l
oss: 0.0761 - val_acc: 0.9760
Epoch 6/20
60000/60000 [==============================] - 25s 423us/step - loss: 0.1160 - acc: 0.9641 - val_l
oss: 0.0728 - val_acc: 0.9768
Epoch 7/20
60000/60000 [==============================] - 23s 383us/step - loss: 0.1060 - acc: 0.9669 - val_l
oss: 0.0684 - val_acc: 0.9792
Epoch 8/20
60000/60000 [==============================] - 21s 348us/step - loss: 0.0953 - acc: 0.9696 - val_l
oss: 0.0629 - val_acc: 0.9792
Epoch 9/20
60000/60000 [==============================] - 26s 426us/step - loss: 0.0932 - acc: 0.9709 - val_l
oss: 0.0614 - val_acc: 0.9811
Epoch 10/20
60000/60000 [==============================] - 25s 408us/step - loss: 0.0855 - acc: 0.9730 - val_l
oss: 0.0650 - val_acc: 0.9802
Epoch 11/20
60000/60000 [==============================] - 26s 427us/step - loss: 0.0809 - acc: 0.9744 - val_l
oss: 0.0625 - val_acc: 0.9807
Epoch 12/20
60000/60000 [==============================] - 25s 425us/step - loss: 0.0775 - acc: 0.9753 - val_l
oss: 0.0615 - val_acc: 0.9813
Epoch 13/20
60000/60000 [==============================] - 25s 419us/step - loss: 0.0729 - acc: 0.9766 - val_l
oss: 0.0596 - val_acc: 0.9814
Epoch 14/20
60000/60000 [==============================] - 25s 420us/step - loss: 0.0690 - acc: 0.9775 - val_l
oss: 0.0581 - val_acc: 0.9817
Epoch 15/20
60000/60000 [==============================] - 25s 417us/step - loss: 0.0678 - acc: 0.9786 - val_l
oss: 0.0576 - val_acc: 0.9821
Epoch 16/20
60000/60000 [==============================] - 25s 421us/step - loss: 0.0635 - acc: 0.9796 - val_l
oss: 0.0610 - val_acc: 0.9821
Epoch 17/20
60000/60000 [==============================] - 26s 427us/step - loss: 0.0611 - acc: 0.9803 - val_l
oss: 0.0599 - val_acc: 0.9831
Epoch 18/20
60000/60000 [==============================] - 25s 416us/step - loss: 0.0594 - acc: 0.9808 - val_l
oss: 0.0568 - val_acc: 0.9836
Epoch 19/20
60000/60000 [==============================] - 26s 437us/step - loss: 0.0535 - acc: 0.9824 - val_l
oss: 0.0598 - val_acc: 0.9825
Epoch 20/20
60000/60000 [==============================] - 27s 453us/step - loss: 0.0551 - acc: 0.9819 - val_l
oss: 0.0554 - val_acc: 0.9839
```

In [16]:

```python
score = model_relu.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')

# list of epoch numbers
```

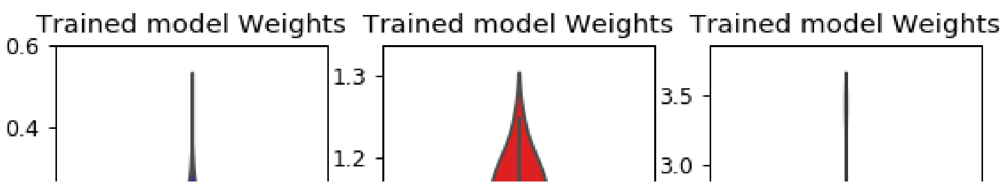
```
x = list(range(1,nb_epoch+1))

vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
```

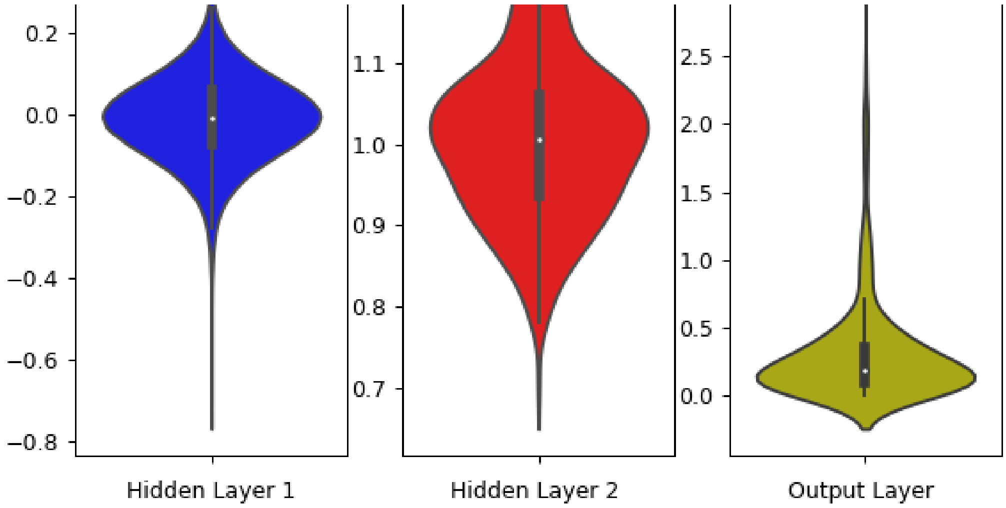
```
Test score: 0.05540496020909195
Test accuracy: 0.9839
```



In [17]:

```
w_after = model_relu.get_weights()

h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
out_w = w_after[4].flatten().reshape(-1,1)


fig = plt.figure()
plt.title("Weight matrices after model trained")
plt.subplot(1, 3, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

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

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





1.2)MLP with 2 hidden layers + Relu + AdamOpltimizer(WithoutBatchNormalisation,Without dropout)

In [25]:

```
model_relu = Sequential()
#Let's take dimension of first and second hidden layer 400 and 250 respectively
# If we sample weights from a normal distribution N(0,σ) we satisfy this condition with
σ=√(2/(ni).
# h1 =>  σ=√(2/(fan_in) = 0.070  => N(0,σ) = N(0,0.070)
# h2 =>  σ=√(2/(fan_in) = 0.089  => N(0,σ) = N(0,0.089)

model_relu.add(Dense(400, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNor
mal(mean=0.0, stddev=0.070, seed=None)))
model_relu.add(Dense(250, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.089
, seed=None)) )
model_relu.add(Dense(output_dim, activation='softmax'))

model_relu.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_14 (Dense)             (None, 400)               314000    
_________________________________________________________________
dense_15 (Dense)             (None, 250)               100250    
_________________________________________________________________
dense_16 (Dense)             (None, 10)                2510      
=================================================================
Total params: 416,760
Trainable params: 416,760
Non-trainable params: 0
_________________________________________________________________
```

In [26]:

```
#Applying adam optimizer
model_relu.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history = model_relu.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, valid
ation_data=(X_test, Y_test))
```

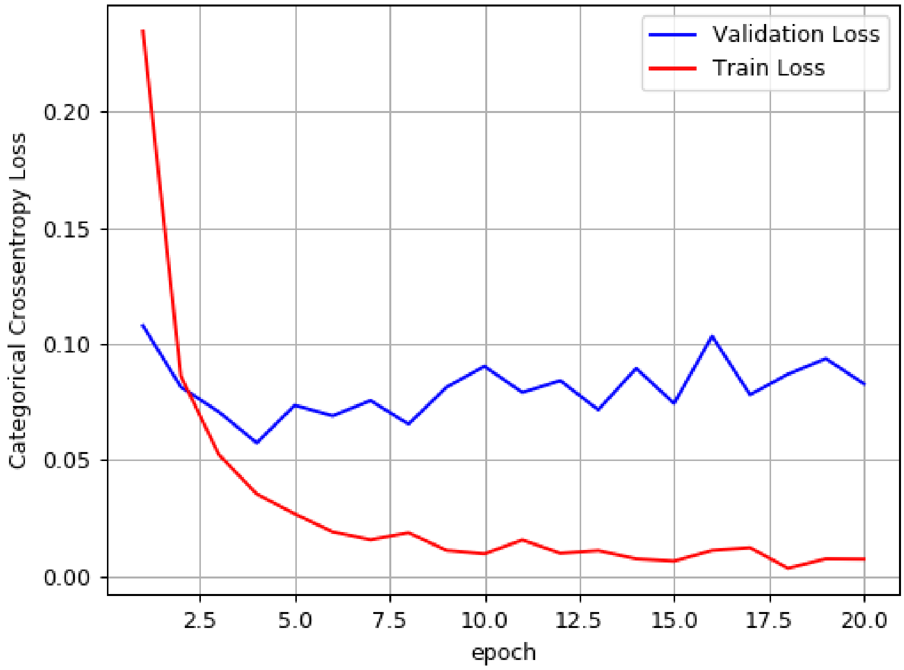
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 9s 150us/step - loss: 0.2348 - acc: 0.9305 -
val_loss: 0.1079 - val_acc: 0.9656
Epoch 2/20
60000/60000 [==============================] - 9s 146us/step - loss: 0.0862 - acc: 0.9738 -
val_loss: 0.0815 - val_acc: 0.9747
Epoch 3/20
60000/60000 [==============================] - 9s 153us/step - loss: 0.0524 - acc: 0.9835 -
val_loss: 0.0708 - val_acc: 0.9776
```

```
Epoch 4/20
60000/60000 [==============================] - 9s 156us/step - loss: 0.0353 - acc: 0.9889 -
val_loss: 0.0574 - val_acc: 0.9824
Epoch 5/20
60000/60000 [==============================] - 9s 151us/step - loss: 0.0268 - acc: 0.9908 -
val_loss: 0.0736 - val_acc: 0.9772
Epoch 6/20
60000/60000 [==============================] - 9s 153us/step - loss: 0.0190 - acc: 0.9940 -
val_loss: 0.0690 - val_acc: 0.9804
Epoch 7/20
60000/60000 [==============================] - 9s 152us/step - loss: 0.0156 - acc: 0.9949 -
val_loss: 0.0756 - val_acc: 0.9768
Epoch 8/20
60000/60000 [==============================] - 9s 156us/step - loss: 0.0186 - acc: 0.9935 -
val_loss: 0.0655 - val_acc: 0.9808
Epoch 9/20
60000/60000 [==============================] - 9s 153us/step - loss: 0.0111 - acc: 0.9963 -
val_loss: 0.0814 - val_acc: 0.9782
Epoch 10/20
60000/60000 [==============================] - 10s 159us/step - loss: 0.0096 - acc: 0.9971 - val_l
oss: 0.0904 - val_acc: 0.9786
Epoch 11/20
60000/60000 [==============================] - 9s 155us/step - loss: 0.0155 - acc: 0.9946 -
val_loss: 0.0791 - val_acc: 0.9798
Epoch 12/20
60000/60000 [==============================] - 9s 156us/step - loss: 0.0098 - acc: 0.9966 -
val_loss: 0.0842 - val_acc: 0.9789
Epoch 13/20
60000/60000 [==============================] - 9s 152us/step - loss: 0.0110 - acc: 0.9964 -
val_loss: 0.0717 - val_acc: 0.9821
Epoch 14/20
60000/60000 [==============================] - 9s 155us/step - loss: 0.0074 - acc: 0.9977 -
val_loss: 0.0895 - val_acc: 0.9803
Epoch 15/20
60000/60000 [==============================] - 10s 172us/step - loss: 0.0065 - acc: 0.9979 - val_l
oss: 0.0744 - val_acc: 0.9832
Epoch 16/20
60000/60000 [==============================] - 12s 194us/step - loss: 0.0110 - acc: 0.9965 - val_l
oss: 0.1034 - val_acc: 0.9791
Epoch 17/20
60000/60000 [==============================] - 10s 161us/step - loss: 0.0122 - acc: 0.9958 - val_l
oss: 0.0782 - val_acc: 0.9802
Epoch 18/20
60000/60000 [==============================] - 10s 165us/step - loss: 0.0034 - acc: 0.9991 - val_l
oss: 0.0870 - val_acc: 0.9821
Epoch 19/20
60000/60000 [==============================] - 10s 173us/step - loss: 0.0074 - acc: 0.9973 - val_l
oss: 0.0937 - val_acc: 0.9791
Epoch 20/20
60000/60000 [==============================] - 11s 186us/step - loss: 0.0073 - acc: 0.9975 - val_l
oss: 0.0829 - val_acc: 0.9835
```

In [27]:

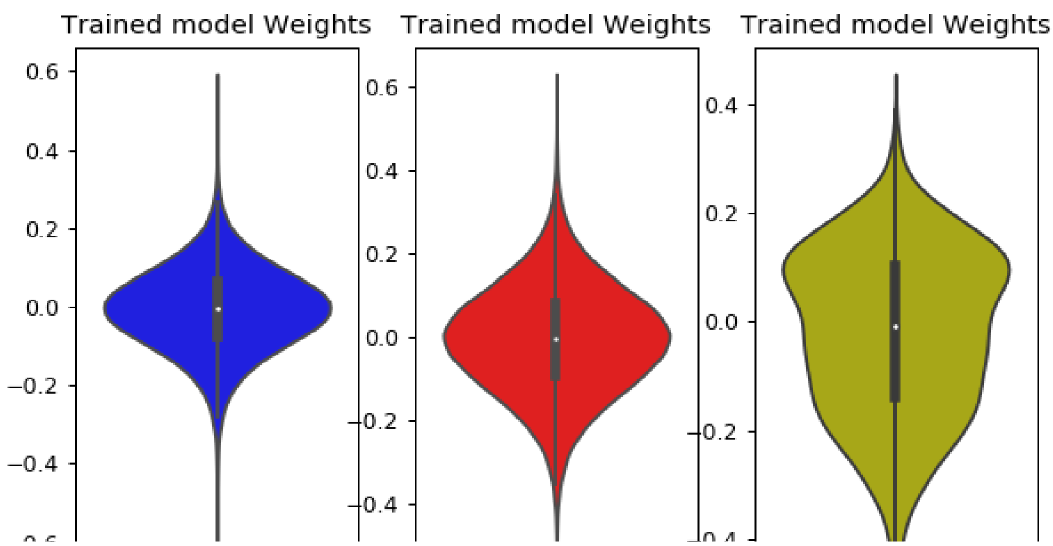
```python
score = model_relu.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')

# list of epoch numbers
x = list(range(1,nb_epoch+1))

vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
```

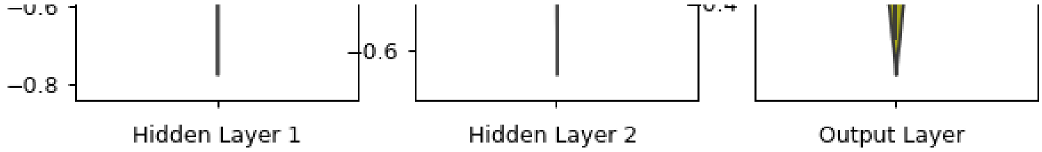
```
Test score: 0.08285639366751603
Test accuracy: 0.9835
```



In [28]:

```
w_after = model_relu.get_weights()

h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
out_w = w_after[4].flatten().reshape(-1,1)


fig = plt.figure()
plt.title("Weight matrices after model trained")
plt.subplot(1, 3, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

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

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





2.1)MLP with 3 hidden layers + Relu + BatchNormalisation+Dropout + AdamOpltimizer

In [18]:

```
model_relu = Sequential()
#Let's take dimension of first, second and third hidden layer 480, 280 and 80 respectively
# If we sample weights from a normal distribution N(0,σ) we satisfy this condition with
σ=√(2/(ni).
# h1 =>  σ=√(2/(fan_in) = 0.064  => N(0,σ) = N(0,0.064)
# h2 =>  σ=√(2/(fan_in) = 0.084  => N(0,σ) = N(0,0.084)
# h3 =>  σ=√(2/(fan_in) = 0.158  => N(0,σ) = N(0,0.158)

model_relu.add(Dense(480, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNor
mal(mean=0.0, stddev=0.064, seed=None)))
model_relu.add(Dropout(0.5))
model_relu.add(BatchNormalization())

model_relu.add(Dense(280, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.084
, seed=None)) )
model_relu.add(Dropout(0.5))

model_relu.add(Dense(80, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.158,
seed=None)) )
model_relu.add(Dropout(0.5))
model_relu.add(Dense(output_dim, activation='softmax'))

model_relu.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_7 (Dense)              (None, 480)               376800    
_________________________________________________________________
dropout_5 (Dropout)          (None, 480)               0         
_________________________________________________________________
batch_normalization_5 (Batch (None, 480)               1920      
_________________________________________________________________
dense_8 (Dense)              (None, 280)               134680    
_________________________________________________________________
dropout_6 (Dropout)          (None, 280)               0         
_________________________________________________________________
dense_9 (Dense)              (None, 80)                22480     
_________________________________________________________________
dropout_7 (Dropout)          (None, 80)                0         
_________________________________________________________________
dense_10 (Dense)             (None, 10)                810       
=================================================================
Total params: 536,690
Trainable params: 535,730
Non-trainable params: 960
_________________________________________________________________
```

In [19]:

```
#Applying adam optimizer
model_relu.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history = model_relu.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, valid
ation_data=(X_test, Y_test))
```

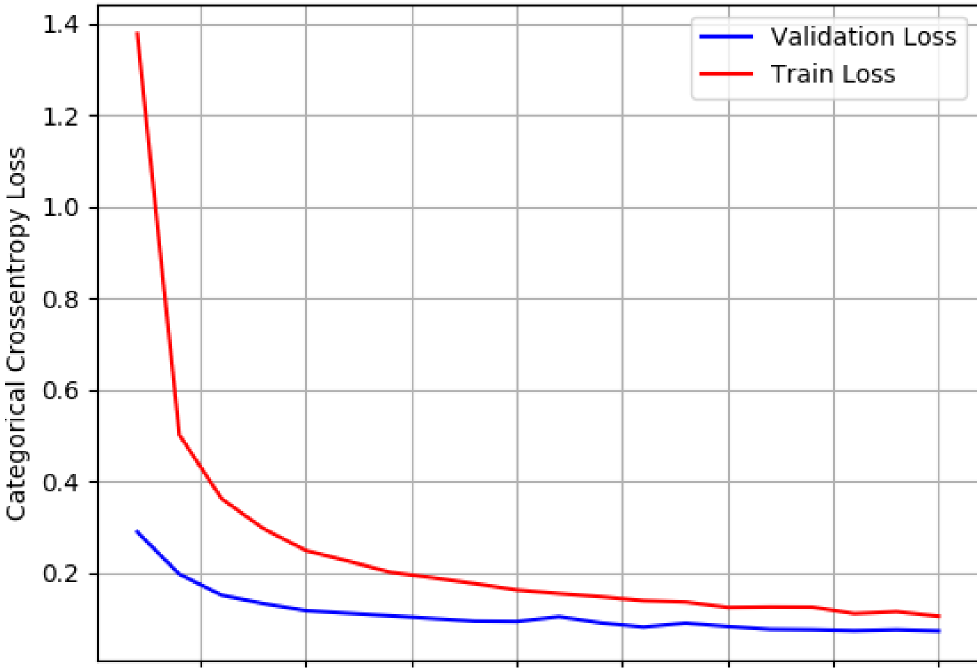
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 24s 405us/step - loss: 1.3775 - acc: 0.6410 - val_l
oss: 0.2898 - val_acc: 0.9212
Epoch 2/20
```

```
60000/60000 [==============================] - 31s 517us/step - loss: 0.5014 - acc: 0.8528 - val_l
oss: 0.1975 - val_acc: 0.9427
Epoch 3/20
60000/60000 [==============================] - 35s 587us/step - loss: 0.3625 - acc: 0.8976 - val_l
oss: 0.1517 - val_acc: 0.9554
Epoch 4/20
60000/60000 [==============================] - 31s 513us/step - loss: 0.2964 - acc: 0.9192 - val_l
oss: 0.1333 - val_acc: 0.9603
Epoch 5/20
60000/60000 [==============================] - 32s 528us/step - loss: 0.2493 - acc: 0.9306 - val_l
oss: 0.1180 - val_acc: 0.9636
Epoch 6/20
60000/60000 [==============================] - 33s 553us/step - loss: 0.2262 - acc: 0.9384 - val_l
oss: 0.1123 - val_acc: 0.9674
Epoch 7/20
60000/60000 [==============================] - 32s 536us/step - loss: 0.2018 - acc: 0.9448 - val_l
oss: 0.1069 - val_acc: 0.9704
Epoch 8/20
60000/60000 [==============================] - 29s 488us/step - loss: 0.1898 - acc: 0.9481 - val_l
oss: 0.1008 - val_acc: 0.9716
Epoch 9/20
60000/60000 [==============================] - 31s 524us/step - loss: 0.1771 - acc: 0.9525 - val_l
oss: 0.0951 - val_acc: 0.9729
Epoch 10/20
60000/60000 [==============================] - 31s 522us/step - loss: 0.1630 - acc: 0.9562 - val_l
oss: 0.0943 - val_acc: 0.9740
Epoch 11/20
60000/60000 [==============================] - 34s 565us/step - loss: 0.1552 - acc: 0.9577 - val_l
oss: 0.1048 - val_acc: 0.9727
Epoch 12/20
60000/60000 [==============================] - 32s 527us/step - loss: 0.1483 - acc: 0.9602 - val_l
oss: 0.0912 - val_acc: 0.9750
Epoch 13/20
60000/60000 [==============================] - 34s 559us/step - loss: 0.1397 - acc: 0.9620 - val_l
oss: 0.0821 - val_acc: 0.9766
Epoch 14/20
60000/60000 [==============================] - 31s 514us/step - loss: 0.1369 - acc: 0.9625 - val_l
oss: 0.0909 - val_acc: 0.9764
Epoch 15/20
60000/60000 [==============================] - 30s 505us/step - loss: 0.1251 - acc: 0.9641 - val_l
oss: 0.0833 - val_acc: 0.9769
Epoch 16/20
60000/60000 [==============================] - 31s 514us/step - loss: 0.1261 - acc: 0.9653 - val_l
oss: 0.0772 - val_acc: 0.9779
Epoch 17/20
60000/60000 [==============================] - 26s 440us/step - loss: 0.1258 - acc: 0.9661 - val_l
oss: 0.0764 - val_acc: 0.9779
Epoch 18/20
60000/60000 [==============================] - 17s 284us/step - loss: 0.1116 - acc: 0.9688 - val_l
oss: 0.0743 - val_acc: 0.9796
Epoch 19/20
60000/60000 [==============================] - 18s 303us/step - loss: 0.1157 - acc: 0.9679 - val_l
oss: 0.0762 - val_acc: 0.9798
Epoch 20/20
60000/60000 [==============================] - 14s 225us/step - loss: 0.1058 - acc: 0.9701 - val_l
oss: 0.0738 - val_acc: 0.9809
```

In [20]:

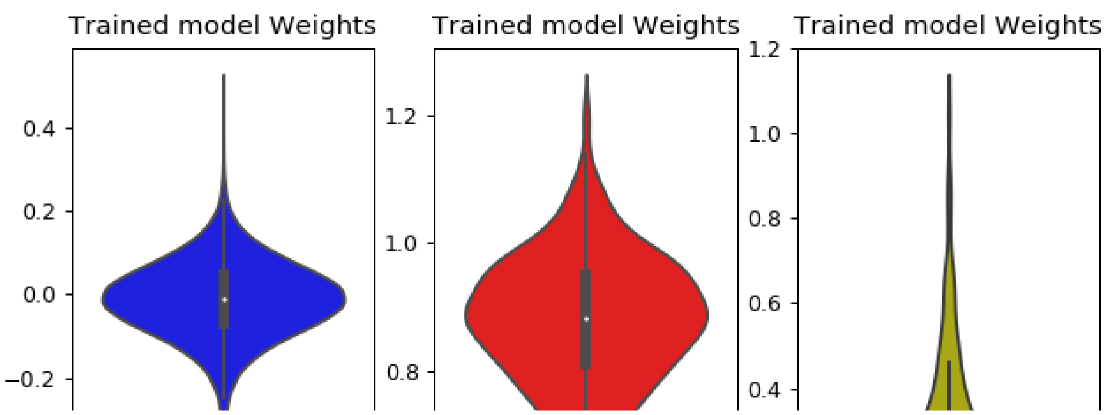
```
score = model_relu.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')

# list of epoch numbers
x = list(range(1,nb_epoch+1))

vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
```

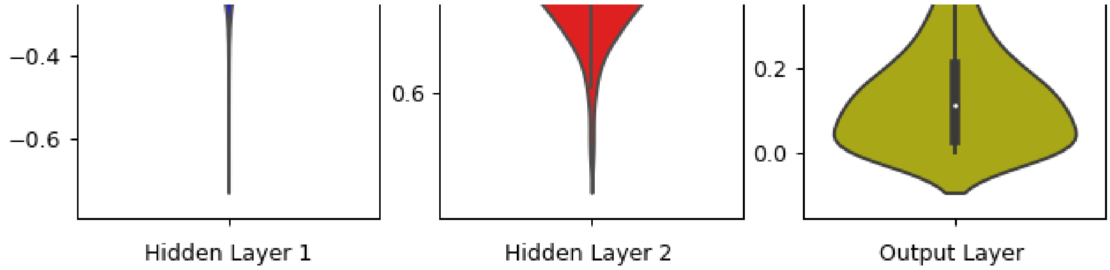
```
Test score: 0.0738352784443341
Test accuracy: 0.9809
```



In [21]:

```
w_after = model_relu.get_weights()

h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
out_w = w_after[4].flatten().reshape(-1,1)


fig = plt.figure()
plt.title("Weight matrices after model trained")
plt.subplot(1, 3, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

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

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





2.2)MLP with 3 hidden layers + Relu + AdamOpltimizer(WithoutBatchNormalisation,Without dropout)

In [29]:

```
model_relu = Sequential()
#Let's take dimension of first, second and third hidden layer 480, 280 and 80 respectively
# If we sample weights from a normal distribution N(0,σ) we satisfy this condition with
σ=√(2/(ni).
# h1 =>  σ=√(2/(fan_in) = 0.064  => N(0,σ) = N(0,0.064)
# h2 =>  σ=√(2/(fan_in) = 0.084  => N(0,σ) = N(0,0.084)
# h3 =>  σ=√(2/(fan_in) = 0.158  => N(0,σ) = N(0,0.158)

model_relu.add(Dense(480, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNor
mal(mean=0.0, stddev=0.064, seed=None)))

model_relu.add(Dense(280, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.084
, seed=None)) )

model_relu.add(Dense(80, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.158,
seed=None)) )
model_relu.add(Dense(output_dim, activation='softmax'))

model_relu.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_17 (Dense)             (None, 480)               376800    
_________________________________________________________________
dense_18 (Dense)             (None, 280)               134680    
_________________________________________________________________
dense_19 (Dense)             (None, 80)                22480     
_________________________________________________________________
dense_20 (Dense)             (None, 10)                810       
=================================================================
Total params: 534,770
Trainable params: 534,770
Non-trainable params: 0
_________________________________________________________________
```

In [30]:

```
#Applying adam optimizer
model_relu.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history = model_relu.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, valid
ation_data=(X_test, Y_test))
```

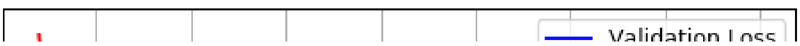
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 12s 205us/step - loss: 0.2225 - acc: 0.9318 - val_l
oss: 0.1375 - val_acc: 0.9572
Epoch 2/20
60000/60000 [==============================] - 11s 188us/step - loss: 0.0835 - acc: 0.9741 - val_l
oss: 0.0897 - val_acc: 0.9718
Epoch 3/20
60000/60000 [==============================] - 12s 193us/step - loss: 0.0514 - acc: 0.9833 - val_l
oss: 0.0896 - val_acc: 0.9724
Epoch 4/20
60000/60000 [==============================] - 12s 192us/step - loss: 0.0386 - acc: 0.9873 - val_l
```

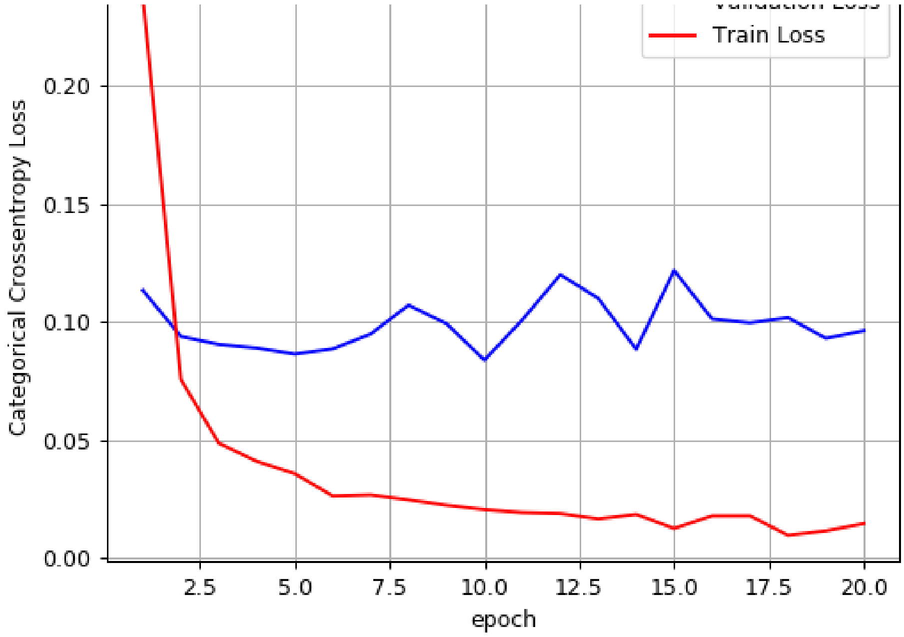
```
60000/60000 [==============================] - 12s 192us/step - loss: 0.0386 - acc: 0.9873 - val_l
oss: 0.0933 - val_acc: 0.9731
Epoch 5/20
60000/60000 [==============================] - 12s 206us/step - loss: 0.0288 - acc: 0.9906 - val_l
oss: 0.0727 - val_acc: 0.9804
Epoch 6/20
60000/60000 [==============================] - 11s 189us/step - loss: 0.0218 - acc: 0.9930 - val_l
oss: 0.0835 - val_acc: 0.9777
Epoch 7/20
60000/60000 [==============================] - 11s 191us/step - loss: 0.0216 - acc: 0.9930 - val_l
oss: 0.0931 - val_acc: 0.9751
Epoch 8/20
60000/60000 [==============================] - 12s 194us/step - loss: 0.0192 - acc: 0.9935 - val_l
oss: 0.0788 - val_acc: 0.9787
Epoch 9/20
60000/60000 [==============================] - 11s 189us/step - loss: 0.0157 - acc: 0.9950 - val_l
oss: 0.0809 - val_acc: 0.9792
Epoch 10/20
60000/60000 [==============================] - 11s 189us/step - loss: 0.0185 - acc: 0.9940 - val_l
oss: 0.0821 - val_acc: 0.9801
Epoch 11/20
60000/60000 [==============================] - 11s 190us/step - loss: 0.0120 - acc: 0.9960 - val_l
oss: 0.0985 - val_acc: 0.9783
Epoch 12/20
60000/60000 [==============================] - 11s 184us/step - loss: 0.0161 - acc: 0.9949 - val_l
oss: 0.0820 - val_acc: 0.9802
Epoch 13/20
60000/60000 [==============================] - 11s 191us/step - loss: 0.0117 - acc: 0.9960 - val_l
oss: 0.0742 - val_acc: 0.9824
Epoch 14/20
60000/60000 [==============================] - 11s 187us/step - loss: 0.0119 - acc: 0.9963 - val_l
oss: 0.0831 - val_acc: 0.9829
Epoch 15/20
60000/60000 [==============================] - 12s 197us/step - loss: 0.0133 - acc: 0.9960 - val_l
oss: 0.1034 - val_acc: 0.9775
Epoch 16/20
60000/60000 [==============================] - 12s 200us/step - loss: 0.0122 - acc: 0.9963 - val_l
oss: 0.0914 - val_acc: 0.9804
Epoch 17/20
60000/60000 [==============================] - 12s 202us/step - loss: 0.0097 - acc: 0.9970 - val_l
oss: 0.0945 - val_acc: 0.9805
Epoch 18/20
60000/60000 [==============================] - 12s 201us/step - loss: 0.0094 - acc: 0.9970 - val_l
oss: 0.0982 - val_acc: 0.9825
Epoch 19/20
60000/60000 [==============================] - 13s 223us/step - loss: 0.0099 - acc: 0.9970 - val_l
oss: 0.1012 - val_acc: 0.9795
Epoch 20/20
60000/60000 [==============================] - 12s 202us/step - loss: 0.0108 - acc: 0.9966 - val_l
oss: 0.0948 - val_acc: 0.9814
```

In [19]:

```
score = model_relu.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')

# list of epoch numbers
x = list(range(1,nb_epoch+1))

vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
```

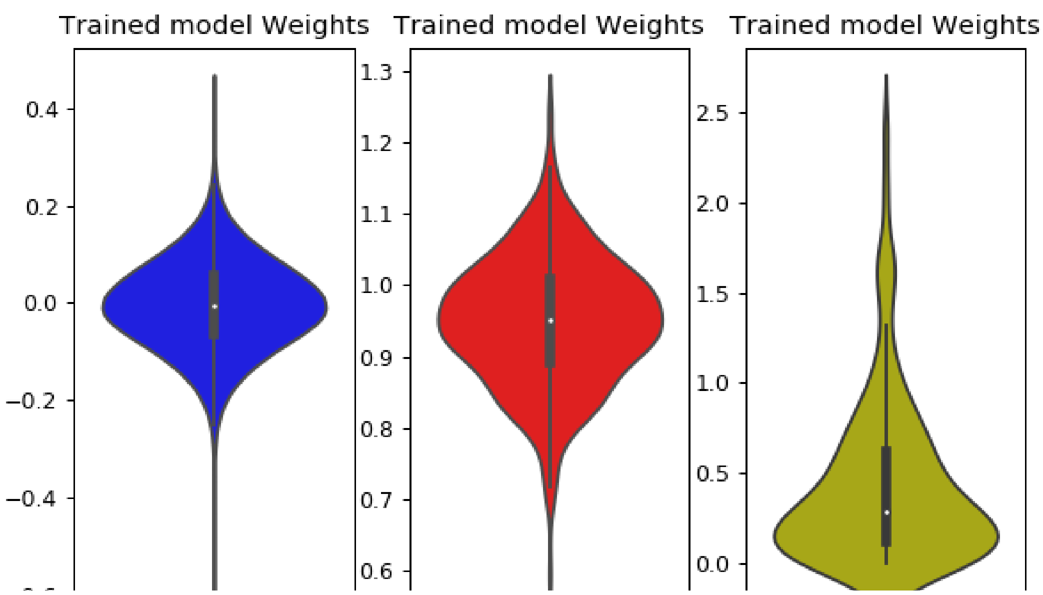
```
Test score: 0.09616601888963419
Test accuracy: 0.9786
```

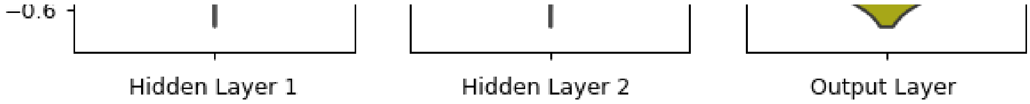




In [20]:

```
w_after = model_relu.get_weights()

h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
out_w = w_after[4].flatten().reshape(-1,1)


fig = plt.figure()
plt.title("Weight matrices after model trained")
plt.subplot(1, 3, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

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

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





3.1)MLP with 5 hidden layers + Relu + BatchNormalisation +Dropout+ AdamOpltimizer

In [22]:

```
model_relu = Sequential()
#Let's take dimension of first, second,third,fourth and fifth hidden layer 650,550,400,200 and 100
respectively
# If we sample weights from a normal distribution N(0,σ) we satisfy this condition with
σ=√(2/(ni).
# h1 =>  σ=√(2/(fan_in) = 0.055  => N(0,σ) = N(0,0.055)
# h2 =>  σ=√(2/(fan_in) = 0.060  => N(0,σ) = N(0,0.060)
# h3 =>  σ=√(2/(fan_in) = 0.070  => N(0,σ) = N(0,0.070)
# h4 =>  σ=√(2/(fan_in) = 0.1  => N(0,σ) = N(0,0.1)
# h5 =>  σ=√(2/(fan_in) = 0.141  => N(0,σ) = N(0,0.141)

model_relu.add(Dense(650, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNor
mal(mean=0.0, stddev=0.055, seed=None)))
model_relu.add(Dropout(0.5))

model_relu.add(Dense(550, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.060
, seed=None)) )
model_relu.add(BatchNormalization())
model_relu.add(Dropout(0.5))

model_relu.add(Dense(400, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.070
, seed=None)) )
model_relu.add(Dropout(0.5))

model_relu.add(Dense(200, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.1,
seed=None)) )
model_relu.add(BatchNormalization())
model_relu.add(Dropout(0.5))

model_relu.add(Dense(100, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.141
, seed=None)) )
model_relu.add(Dropout(0.5))

model_relu.add(Dense(output_dim, activation='softmax'))

model_relu.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_11 (Dense)             (None, 650)               510250    
_________________________________________________________________
dropout_8 (Dropout)          (None, 650)               0         
_________________________________________________________________
dense_12 (Dense)             (None, 550)               358050    
_________________________________________________________________
batch_normalization_6 (Batch (None, 550)               2200      
_________________________________________________________________
dropout_9 (Dropout)          (None, 550)               0         
_________________________________________________________________
dense_13 (Dense)             (None, 400)               220400    
_________________________________________________________________
dropout_10 (Dropout)         (None, 400)               0         
_________________________________________________________________
dense_14 (Dense)             (None, 200)               80200     
_________________________________________________________________
batch_normalization_7 (Batch (None, 200)               800       
_________________________________________________________________
dropout_11 (Dropout)         (None, 200)               0         
_________________________________________________________________
dense_15 (Dense)             (None, 100)               20100     
_________________________________________________________________
dropout_12 (Dropout)         (None, 100)               0         
_________________________________________________________________
```

```
dense_16 (Dense)             (None, 10)                1010      
=================================================================
Total params: 1,193,010
Trainable params: 1,191,510
Non-trainable params: 1,500
_________________________________________________________________
```

In [23]:

```python
#Applying adam optimizer
model_relu.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
history = model_relu.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, validation_data=(X_test, Y_test))
```

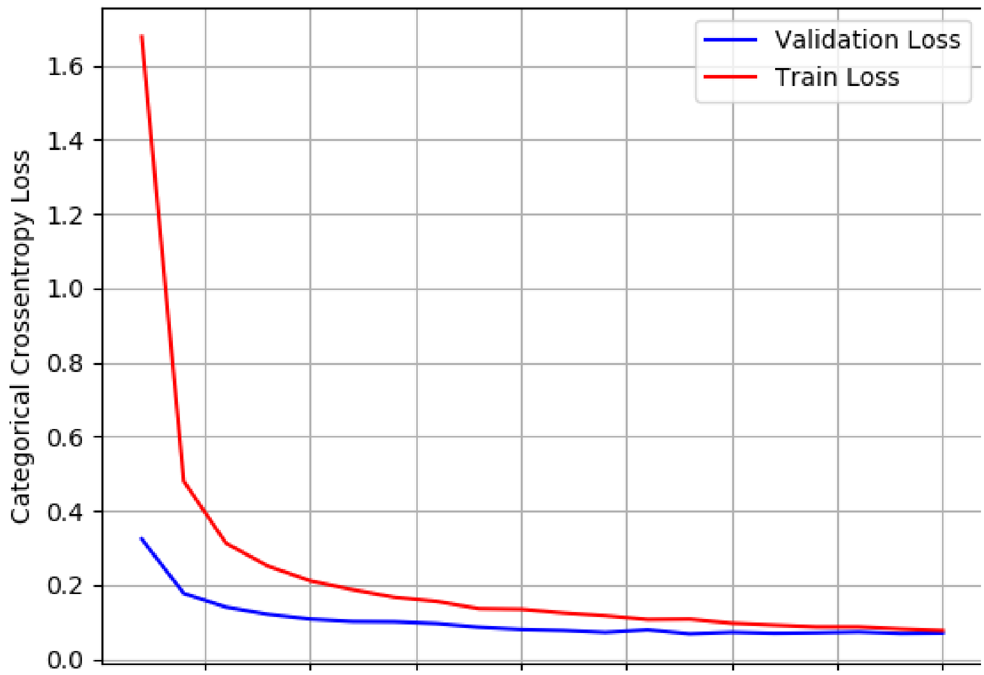
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 44s 731us/step - loss: 1.6782 - acc: 0.5578 - val_loss: 0.3243 - val_acc: 0.9075
Epoch 2/20
60000/60000 [==============================] - 40s 668us/step - loss: 0.4796 - acc: 0.8577 - val_loss: 0.1773 - val_acc: 0.9468
Epoch 3/20
60000/60000 [==============================] - 30s 493us/step - loss: 0.3129 - acc: 0.9120 - val_loss: 0.1405 - val_acc: 0.9598
Epoch 4/20
60000/60000 [==============================] - 41s 682us/step - loss: 0.2509 - acc: 0.9321 - val_loss: 0.1210 - val_acc: 0.9663
Epoch 5/20
60000/60000 [==============================] - 35s 579us/step - loss: 0.2115 - acc: 0.9434 - val_loss: 0.1080 - val_acc: 0.9698
Epoch 6/20
60000/60000 [==============================] - 40s 673us/step - loss: 0.1874 - acc: 0.9506 - val_loss: 0.1018 - val_acc: 0.9710
Epoch 7/20
60000/60000 [==============================] - 46s 767us/step - loss: 0.1670 - acc: 0.9552 - val_loss: 0.1011 - val_acc: 0.9731
Epoch 8/20
60000/60000 [==============================] - 44s 727us/step - loss: 0.1559 - acc: 0.9591 - val_loss: 0.0960 - val_acc: 0.9733
Epoch 9/20
60000/60000 [==============================] - 45s 748us/step - loss: 0.1363 - acc: 0.9638 - val_loss: 0.0863 - val_acc: 0.9774
Epoch 10/20
60000/60000 [==============================] - 36s 593us/step - loss: 0.1348 - acc: 0.9644 - val_loss: 0.0803 - val_acc: 0.9780
Epoch 11/20
60000/60000 [==============================] - 36s 593us/step - loss: 0.1247 - acc: 0.9671 - val_loss: 0.0776 - val_acc: 0.9789
Epoch 12/20
60000/60000 [==============================] - 46s 768us/step - loss: 0.1171 - acc: 0.9681 - val_loss: 0.0723 - val_acc: 0.9805
Epoch 13/20
60000/60000 [==============================] - 42s 707us/step - loss: 0.1069 - acc: 0.9714 - val_loss: 0.0793 - val_acc: 0.9794
Epoch 14/20
60000/60000 [==============================] - 37s 621us/step - loss: 0.1078 - acc: 0.9724 - val_loss: 0.0683 - val_acc: 0.9827
Epoch 15/20
60000/60000 [==============================] - 34s 568us/step - loss: 0.0970 - acc: 0.9746 - val_loss: 0.0725 - val_acc: 0.9820
Epoch 16/20
60000/60000 [==============================] - 33s 557us/step - loss: 0.0920 - acc: 0.9749 - val_loss: 0.0698 - val_acc: 0.9823
Epoch 17/20
60000/60000 [==============================] - 37s 618us/step - loss: 0.0776 - acc: 0.9787 - val_loss: 0.0704 - val_acc: 0.9829
```

In [24]:

```python
score = model_relu.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')
```

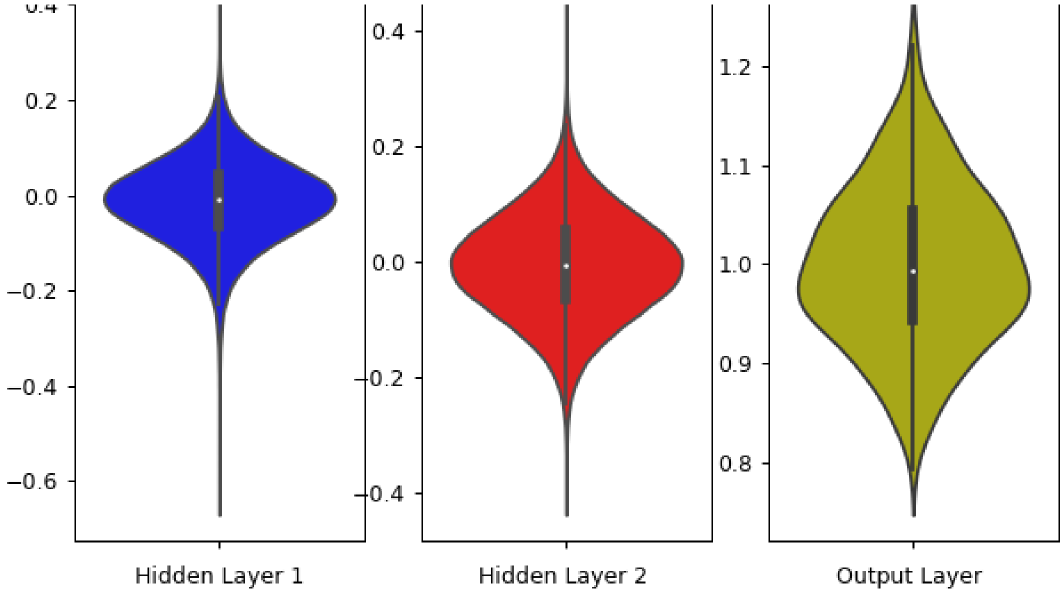
```
ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')

# list of epoch numbers
x = list(range(1,nb_epoch+1))

vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
```

```
Test score: 0.07039678009253549
Test accuracy: 0.9829
```



In [25]:

```
w_after = model_relu.get_weights()

h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
out_w = w_after[4].flatten().reshape(-1,1)


fig = plt.figure()
plt.title("Weight matrices after model trained")
plt.subplot(1, 3, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

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

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



3.2)MLP with 2 hidden layers + Relu + AdamOpltimizer(WithoutBatchNormalisation,Without dropout)

In [21]:

```
model_relu = Sequential()
#Let's take dimension of first, second,third,fourth and fifth hidden layer 650,550,400,200 and 100
respectively
# If we sample weights from a normal distribution N(0,σ) we satisfy this condition with
σ=√(2/(ni).
# h1 =>  σ=√(2/(fan_in) = 0.055  => N(0,σ) = N(0,0.055)
# h2 =>  σ=√(2/(fan_in) = 0.060  => N(0,σ) = N(0,0.060)
# h3 =>  σ=√(2/(fan_in) = 0.070  => N(0,σ) = N(0,0.070)
# h4 =>  σ=√(2/(fan_in) = 0.1  => N(0,σ) = N(0,0.1)
# h5 =>  σ=√(2/(fan_in) = 0.141  => N(0,σ) = N(0,0.141)

model_relu.add(Dense(650, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNor
mal(mean=0.0, stddev=0.055, seed=None)))

model_relu.add(Dense(550, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.060
, seed=None)) )

model_relu.add(Dense(400, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.070
, seed=None)) )

model_relu.add(Dense(200, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.1,
seed=None)) )

model_relu.add(Dense(100, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.141
, seed=None)) )

model_relu.add(Dense(output_dim, activation='softmax'))

model_relu.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_8 (Dense)              (None, 650)               510250    
_________________________________________________________________
dense_9 (Dense)              (None, 550)               358050    
_________________________________________________________________
batch_normalization_4 (Batch (None, 550)               2200      
_________________________________________________________________
dense_10 (Dense)             (None, 400)               220400    
_________________________________________________________________
dense_11 (Dense)             (None, 200)               80200     
_________________________________________________________________
batch_normalization_5 (Batch (None, 200)               800       
_________________________________________________________________
```

```
dense_12 (Dense)             (None, 100)               20100
_________________________________________________________________
dense_13 (Dense)             (None, 10)                1010
=================================================================
Total params: 1,193,010
Trainable params: 1,191,510
Non-trainable params: 1,500
_________________________________________________________________
```

In [22]:

```
#Applying adam optimizer
model_relu.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history = model_relu.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, valid
ation_data=(X_test, Y_test))
```

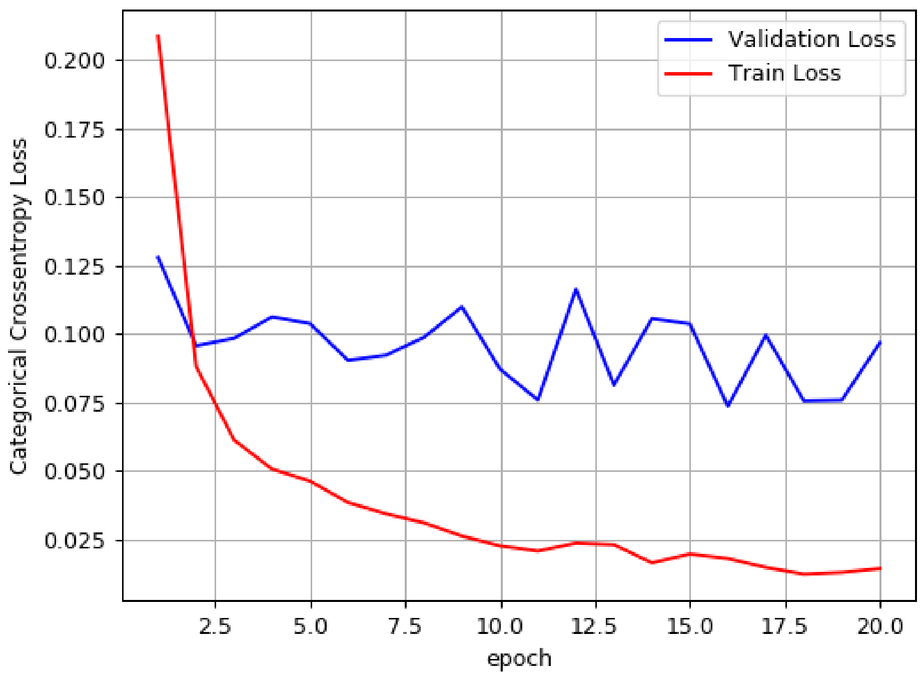
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 21s 344us/step - loss: 0.2085 - acc: 0.9375 - val_l
oss: 0.1278 - val_acc: 0.9608
Epoch 2/20
60000/60000 [==============================] - 20s 330us/step - loss: 0.0881 - acc: 0.9732 - val_l
oss: 0.0956 - val_acc: 0.9712
Epoch 3/20
60000/60000 [==============================] - 20s 330us/step - loss: 0.0612 - acc: 0.9807 - val_l
oss: 0.0983 - val_acc: 0.9704
Epoch 4/20
60000/60000 [==============================] - 20s 333us/step - loss: 0.0505 - acc: 0.9839 - val_l
oss: 0.1061 - val_acc: 0.9701
Epoch 5/20
60000/60000 [==============================] - 23s 386us/step - loss: 0.0462 - acc: 0.9847 - val_l
oss: 0.1037 - val_acc: 0.9705
Epoch 6/20
60000/60000 [==============================] - 27s 446us/step - loss: 0.0383 - acc: 0.9876 - val_l
oss: 0.0902 - val_acc: 0.9744
Epoch 7/20
60000/60000 [==============================] - 28s 460us/step - loss: 0.0342 - acc: 0.9886 - val_l
oss: 0.0921 - val_acc: 0.9758
Epoch 8/20
60000/60000 [==============================] - 28s 463us/step - loss: 0.0309 - acc: 0.9896 - val_l
oss: 0.0986 - val_acc: 0.9735
Epoch 9/20
60000/60000 [==============================] - 33s 546us/step - loss: 0.0261 - acc: 0.9914 - val_l
oss: 0.1098 - val_acc: 0.9700
Epoch 10/20
60000/60000 [==============================] - 34s 567us/step - loss: 0.0225 - acc: 0.9926 - val_l
oss: 0.0871 - val_acc: 0.9771
Epoch 11/20
60000/60000 [==============================] - 30s 506us/step - loss: 0.0206 - acc: 0.9931 - val_l
oss: 0.0758 - val_acc: 0.9795
Epoch 12/20
60000/60000 [==============================] - 31s 512us/step - loss: 0.0235 - acc: 0.9924 - val_l
oss: 0.1162 - val_acc: 0.9711
Epoch 13/20
60000/60000 [==============================] - 28s 464us/step - loss: 0.0230 - acc: 0.9925 - val_l
oss: 0.0812 - val_acc: 0.9799
Epoch 14/20
60000/60000 [==============================] - 28s 472us/step - loss: 0.0164 - acc: 0.9947 - val_l
oss: 0.1055 - val_acc: 0.9749
Epoch 15/20
60000/60000 [==============================] - 28s 460us/step - loss: 0.0195 - acc: 0.9933 - val_l
oss: 0.1036 - val_acc: 0.9780
Epoch 16/20
60000/60000 [==============================] - 28s 467us/step - loss: 0.0179 - acc: 0.9942 - val_l
oss: 0.0735 - val_acc: 0.9821
Epoch 17/20
60000/60000 [==============================] - 27s 452us/step - loss: 0.0147 - acc: 0.9952 - val_l
oss: 0.0994 - val_acc: 0.9771
Epoch 18/20
60000/60000 [==============================] - 29s 481us/step - loss: 0.0122 - acc: 0.9959 - val_l
oss: 0.0755 - val_acc: 0.9822
Epoch 19/20
60000/60000 [==============================] - 28s 473us/step - loss: 0.0128 - acc: 0.9958 - val_l
oss: 0.0757 - val_acc: 0.9820
```

```
Epoch 20/20
60000/60000 [==============================] - 28s 470us/step - loss: 0.0143 - acc: 0.9954 - val_l
oss: 0.0966 - val_acc: 0.9769 - loss: 0.0133 - acc:  -
```

In [23]:

```
score = model_relu.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')

# list of epoch numbers
x = list(range(1,nb_epoch+1))

vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
```

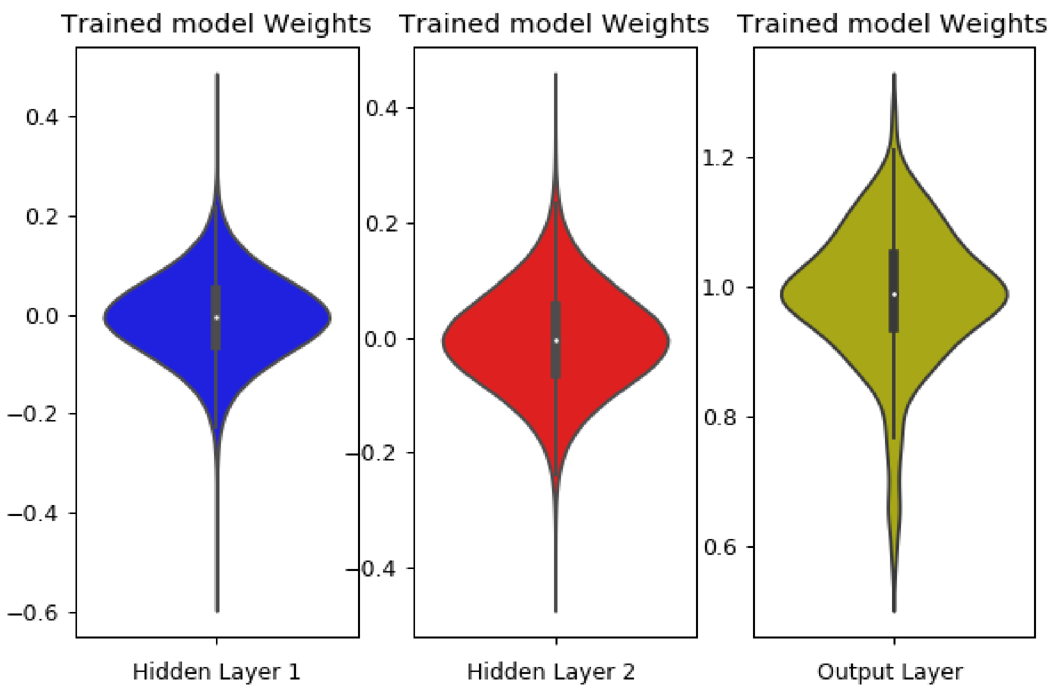
```
Test score: 0.09663725952169334
Test accuracy: 0.9769
```



In [24]:

```
w_after = model_relu.get_weights()

h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
out_w = w_after[4].flatten().reshape(-1,1)


fig = plt.figure()
plt.title("Weight matrices after model trained")
plt.subplot(1, 3, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

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

plt.subplot(1, 3, 3)
```

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



In [32]:

```
x = PrettyTable()
x.field_names = ["No of layer","Dropout&normalizationused", "Accuracy"]
x.add_row(["2","Yes","0.9839"])
x.add_row(["2","No","0.9835"])
x.add_row(["2","Yes","0.9809"])
x.add_row(["3","No","0.9786"])
x.add_row(["3","Yes","0.9829"])
x.add_row(["5","NO","0.9769"])

print(x)
```

```
+-------------+---------------------------+----------+
| No of layer | Dropout&normalizationused | Accuracy |
+-------------+---------------------------+----------+
|      2      |            Yes            |  0.9839  |
|      2      |             No            |  0.9835  |
|      2      |            Yes            |  0.9809  |
|      3      |             No            |  0.9786  |
|      3      |            Yes            |  0.9829  |
|      5      |             NO            |  0.9769  |
+-------------+---------------------------+----------+
```

Conclusion

By the above table we can infer that adding dropouts and by batchnormalizing,performance of the model increases