In [86]:

```
from keras.utils import np_utils #import utilities from the keras
from keras.datasets import mnist #loading mnist dataset
import seaborn as sns #seaborn library for plotting
from keras.initializers import RandomNormal #to intializer weights we have an inbuild keras
library and from that we are importing randomnormal initializer
```

In [87]:

```
%matplotlib inline
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 [88]:

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

In [89]:

```
X_train.shape
```

Out[89]:

```
(60000, 28, 28)
```

In [90]:

```
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 [91]:

```
# 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 [92]:

```
# 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 [93]:

```
# 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   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  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   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]
```

The above matrix is a greyscale image 28*28 pixel image with values ranging from 0 to 255 with 0 as white and as we move from 0 to 255 it turns from white to grey to black

In [94]:

```
# 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 [95]:

```
# 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.        ]
```

In [96]:

```
# 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) #from np.utils we used to the function
to_categorical to convert our output into a one-hot encoded vector
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 [97]:

```
# https://keras.io/getting-started/sequential-model-guide/

# The Sequential model is a linear stack of layers.Each Layer has exactly one input tensor and one
output tensor
# you can create a Sequential model by passing a list of layer instances to the constructor:

# model = Sequential([
#     Dense(32, input_shape=(784,)),
#     Activation('relu'),
#     Dense(10),
#     Activation('softmax'),
# ])

# You can also simply add layers via the .add() method:

# model = Sequential()
# model.add(Dense(32, input_dim=784))
# model.add(Activation('relu'))

###

# https://keras.io/layers/core/

# keras.layers.Dense(units, activation=None, use_bias=True, kernel_initializer='glorot_uniform',
# bias_initializer='zeros', kernel_regularizer=None, bias_regularizer=None,
activity_regularizer=None,
# kernel_constraint=None, bias_constraint=None)

# Dense implements the operation: output = activation(dot(input, kernel) + bias) where
# activation is the element-wise activation function passed as the activation argument,
# kernel is a weights matrix created by the layer, and
# bias is a bias vector created by the layer (only applicable if use_bias is True).

# output = activation(dot(input, kernel) + bias)  => y = activation(WT. X + b)

####

# https://keras.io/activations/

# Activations can either be used through an Activation layer, or through the activation argument s
upported by all forward layers:

# from keras.layers import Activation, Dense

# model.add(Dense(64))
# model.add(Activation('tanh'))

# This is equivalent to:
# model.add(Dense(64, activation='tanh'))

# there are many activation functions ar available ex: tanh, relu, softmax


from keras.models import Sequential #importing a sequential model
from keras.layers import Dense, Activation #importing dense and also activation to use activation
functions
```

In [98]:

```
# some model parameters

output_dim = 10 #since we have to class numbers from 0 to 9 we have output dimension as 10
input_dim = X_train.shape[1] #input dimension will the image i.e. 784(28*28 px image)
print(input_dim)

batch_size = 128 #used a batch size of 128
nb_epoch = 20 #number of epochs is 28
```

```
784
```

ReLU + Adam Optimization + 2 Hidden Layers (without Dropout and Batch Normalization)

Hidden layer 1 consists of 256 outputs and Hidden Layer2 consists of 64 connections

In [99]:

```
model_relu = Sequential()
model_relu.add(Dense(256, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNor
mal(mean=0.0, stddev=0.062, seed=None)))
model_relu.add(Dense(64, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.125,
seed=None)) )
model_relu.add(Dense(output_dim, activation='softmax'))

print(model_relu.summary())

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))
```

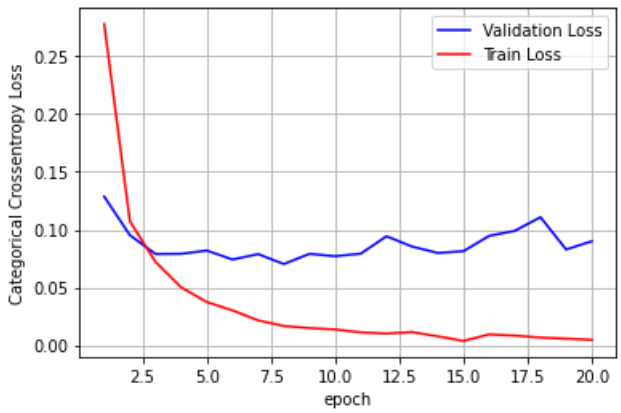
```
Model: "sequential_16"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_59 (Dense)             (None, 256)               200960
_________________________________________________________________
dense_60 (Dense)             (None, 64)                16448
_________________________________________________________________
dense_61 (Dense)             (None, 10)                650
=================================================================
Total params: 218,058
Trainable params: 218,058
Non-trainable params: 0
_________________________________________________________________
None
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.2779 - accuracy: 0.9176 - va
l_loss: 0.1286 - val_accuracy: 0.9611
Epoch 2/20
60000/60000 [==============================] - 3s 53us/step - loss: 0.1073 - accuracy: 0.9682 - va
l_loss: 0.0953 - val_accuracy: 0.9702
Epoch 3/20
60000/60000 [==============================] - 3s 52us/step - loss: 0.0721 - accuracy: 0.9781 - va
l_loss: 0.0790 - val_accuracy: 0.9757
Epoch 4/20
60000/60000 [==============================] - 3s 53us/step - loss: 0.0501 - accuracy: 0.9842 - va
l_loss: 0.0791 - val_accuracy: 0.9752
Epoch 5/20
60000/60000 [==============================] - 3s 53us/step - loss: 0.0373 - accuracy: 0.9883 - va
l_loss: 0.0819 - val_accuracy: 0.9763
Epoch 6/20
60000/60000 [==============================] - 3s 53us/step - loss: 0.0301 - accuracy: 0.9905 - va
l_loss: 0.0742 - val_accuracy: 0.9780
Epoch 7/20
60000/60000 [==============================] - 3s 53us/step - loss: 0.0215 - accuracy: 0.9937 - va
l_loss: 0.0788 - val_accuracy: 0.9775
Epoch 8/20
60000/60000 [==============================] - 3s 53us/step - loss: 0.0167 - accuracy: 0.9951 - va
l_loss: 0.0702 - val_accuracy: 0.9801
Epoch 9/20
60000/60000 [==============================] - 3s 53us/step - loss: 0.0148 - accuracy: 0.9956 - va
l_loss: 0.0791 - val_accuracy: 0.9803
Epoch 10/20
60000/60000 [==============================] - 3s 52us/step - loss: 0.0136 - accuracy: 0.9955 - va
l_loss: 0.0770 - val_accuracy: 0.9803
Epoch 11/20
60000/60000 [==============================] - 3s 52us/step - loss: 0.0112 - accuracy: 0.9964 - va
l_loss: 0.0793 - val_accuracy: 0.9796
Epoch 12/20
60000/60000 [==============================] - 3s 52us/step - loss: 0.0101 - accuracy: 0.9969 - va
l_loss: 0.0943 - val_accuracy: 0.9771
Epoch 13/20
```

```
Epoch 13/20
60000/60000 [==============================] - 3s 52us/step - loss: 0.0114 - accuracy: 0.9962 - va
l_loss: 0.0854 - val_accuracy: 0.9793
Epoch 14/20
60000/60000 [==============================] - 3s 52us/step - loss: 0.0077 - accuracy: 0.9978 - va
l_loss: 0.0798 - val_accuracy: 0.9820
Epoch 15/20
60000/60000 [==============================] - 3s 53us/step - loss: 0.0038 - accuracy: 0.9990 - va
l_loss: 0.0814 - val_accuracy: 0.9826
Epoch 16/20
60000/60000 [==============================] - 3s 53us/step - loss: 0.0094 - accuracy: 0.9966 - va
l_loss: 0.0946 - val_accuracy: 0.9789
Epoch 17/20
60000/60000 [==============================] - 3s 53us/step - loss: 0.0083 - accuracy: 0.9971 - va
l_loss: 0.0990 - val_accuracy: 0.9793
Epoch 18/20
60000/60000 [==============================] - 3s 54us/step - loss: 0.0066 - accuracy: 0.9977 - va
l_loss: 0.1108 - val_accuracy: 0.9767
Epoch 19/20
60000/60000 [==============================] - 3s 52us/step - loss: 0.0057 - accuracy: 0.9983 - va
l_loss: 0.0828 - val_accuracy: 0.9820
Epoch 20/20
60000/60000 [==============================] - 3s 52us/step - loss: 0.0047 - accuracy: 0.9987 - va
l_loss: 0.0900 - val_accuracy: 0.9808
```

In [100]:

```
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))

# print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, va
lidation_data=(X_test, Y_test))

# we will get val_loss and val_acc only when you pass the paramter validation_data
# val_loss : validation loss
# val_acc : validation accuracy

# loss : training loss
# acc : train accuracy
# for each key in histrory.histrory we will have a list of length equal to number of epochs


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

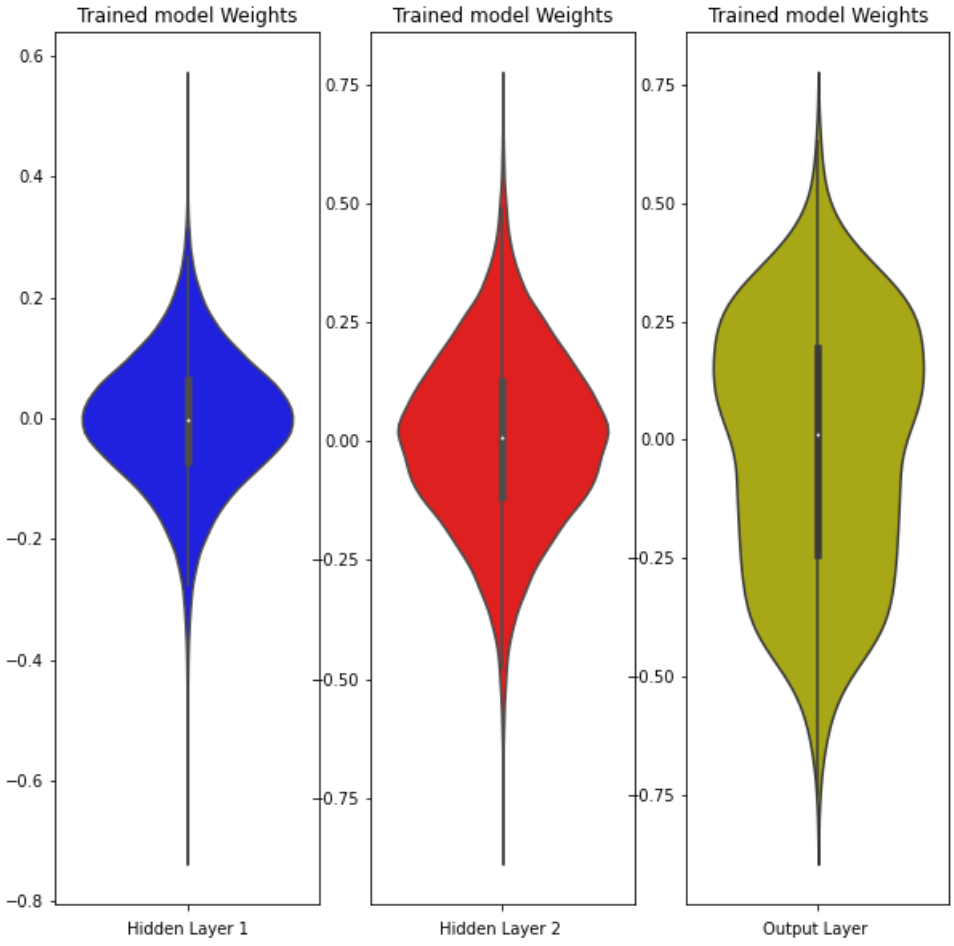
```
Test score: 0.08999803272318979
Test accuracy: 0.9807999730110168
```



after epoch 5 there is not much change in the validation loss whereas our train loss keeps on decreasing around 14 epochs after there is not much change

In [101]:

```
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(figsize=(10,10))
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()
```



ReLU + Adam Optimization + 3 Hidden Layers (without Dropout and Batch Normalization)

Hidden layer 1 consists of 512 outputs and Hidden Layer2 consists of 256 outputs. Hidden Layer

Hidden layer 1 consists of 512 outputs and Hidden Layer2 consists of 256 outputs, Hidden Layer 3 consists of 128 outputs

In [102]:

```
# Multilayer perceptron

model_relu = Sequential() #says we want a sequential model
model_relu.add(Dense(512, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNor
mal(mean=0.0, stddev=0.062, seed=None)))
model_relu.add(Dense(256, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.125
, seed=None)) )
model_relu.add(Dense(128, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.125
, seed=None)) )
model_relu.add(Dense(output_dim, activation='softmax'))

model_relu.summary()#prints the summary
```

```
Model: "sequential_17"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_62 (Dense)             (None, 512)               401920
_________________________________________________________________
dense_63 (Dense)             (None, 256)               131328
_________________________________________________________________
dense_64 (Dense)             (None, 128)               32896
_________________________________________________________________
dense_65 (Dense)             (None, 10)                1290
=================================================================
Total params: 567,434
Trainable params: 567,434
Non-trainable params: 0
_________________________________________________________________
```

In [103]:

```
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))
```

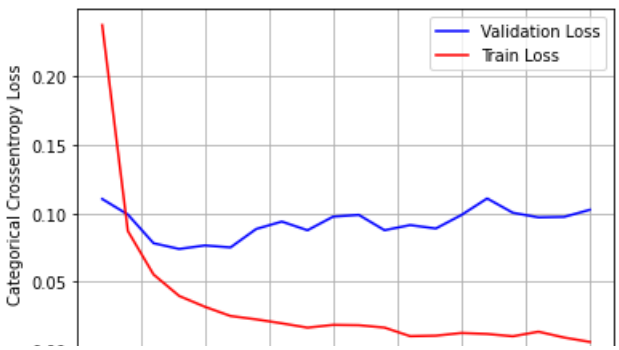
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 7s 121us/step - loss: 0.2373 - accuracy: 0.9292 - v
al_loss: 0.1105 - val_accuracy: 0.9657
Epoch 2/20
60000/60000 [==============================] - 7s 118us/step - loss: 0.0871 - accuracy: 0.9735 - v
al_loss: 0.0991 - val_accuracy: 0.9703
Epoch 3/20
60000/60000 [==============================] - 7s 119us/step - loss: 0.0554 - accuracy: 0.9830 - v
al_loss: 0.0782 - val_accuracy: 0.9770
Epoch 4/20
60000/60000 [==============================] - 7s 118us/step - loss: 0.0397 - accuracy: 0.9877 - v
al_loss: 0.0740 - val_accuracy: 0.9783
Epoch 5/20
60000/60000 [==============================] - 7s 118us/step - loss: 0.0319 - accuracy: 0.9891 - v
al_loss: 0.0766 - val_accuracy: 0.9777
Epoch 6/20
60000/60000 [==============================] - 7s 118us/step - loss: 0.0251 - accuracy: 0.9920 - v
al_loss: 0.0751 - val_accuracy: 0.9794
Epoch 7/20
60000/60000 [==============================] - 7s 119us/step - loss: 0.0227 - accuracy: 0.9925 - v
al_loss: 0.0886 - val_accuracy: 0.9780
Epoch 8/20
60000/60000 [==============================] - 7s 118us/step - loss: 0.0198 - accuracy: 0.9936 - v
al_loss: 0.0940 - val_accuracy: 0.9756
Epoch 9/20
60000/60000 [==============================] - 7s 120us/step - loss: 0.0166 - accuracy: 0.9944 - v
al_loss: 0.0876 - val_accuracy: 0.9764
Epoch 10/20
60000/60000 [==============================] - 7s 119us/step - loss: 0.0186 - accuracy: 0.9940 - v
al_loss: 0.0976 - val_accuracy: 0.9757
Epoch 11/20
60000/60000 [==============================] - 7s 122us/step - loss: 0.0184 - accuracy: 0.9942 - v
```

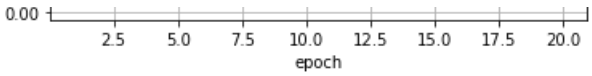
```
al_loss: 0.0989 - val_accuracy: 0.9760
Epoch 12/20
60000/60000 [==============================] - 7s 123us/step - loss: 0.0167 - accuracy: 0.9948 - v
al_loss: 0.0877 - val_accuracy: 0.9793
Epoch 13/20
60000/60000 [==============================] - 7s 122us/step - loss: 0.0104 - accuracy: 0.9966 - v
al_loss: 0.0914 - val_accuracy: 0.9805
Epoch 14/20
60000/60000 [==============================] - 7s 122us/step - loss: 0.0108 - accuracy: 0.9964 - v
al_loss: 0.0889 - val_accuracy: 0.9811
Epoch 15/20
60000/60000 [==============================] - 7s 118us/step - loss: 0.0127 - accuracy: 0.9959 - v
al_loss: 0.0988 - val_accuracy: 0.9780
Epoch 16/20
60000/60000 [==============================] - 7s 121us/step - loss: 0.0120 - accuracy: 0.9959 - v
al_loss: 0.1108 - val_accuracy: 0.9777
Epoch 17/20
60000/60000 [==============================] - 7s 120us/step - loss: 0.0103 - accuracy: 0.9969 - v
al_loss: 0.1004 - val_accuracy: 0.9808
Epoch 18/20
60000/60000 [==============================] - 7s 119us/step - loss: 0.0137 - accuracy: 0.9957 - v
al_loss: 0.0970 - val_accuracy: 0.9785
Epoch 19/20
60000/60000 [==============================] - 7s 120us/step - loss: 0.0094 - accuracy: 0.9970 - v
al_loss: 0.0974 - val_accuracy: 0.9810
Epoch 20/20
60000/60000 [==============================] - 7s 119us/step - loss: 0.0062 - accuracy: 0.9980 - v
al_loss: 0.1026 - val_accuracy: 0.9801
```

In [104]:

```
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))

# print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, va
lidation_data=(X_test, Y_test))

# we will get val_loss and val_acc only when you pass the paramter validation_data
# val_loss : validation loss
# val_acc : validation accuracy

# loss : training loss
# acc : train accuracy
# for each key in histrory.histrory we will have a list of length equal to number of epochs


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

```
Test score: 0.10256570401383279
Test accuracy: 0.9800999760627747
```

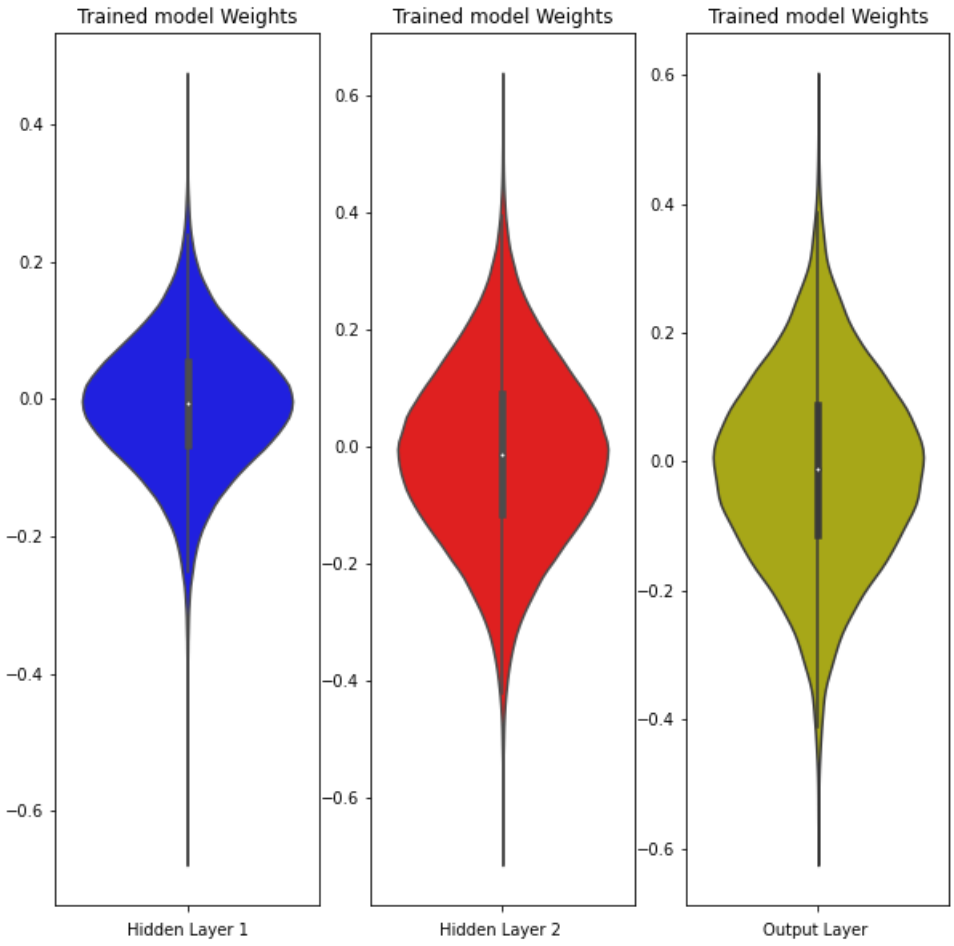




after epoch 3 we ca see jagged lines in our validation loss whereas our train loss keeps on decreasing around 15 epochs after there is not much change

In [105]:

```
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(figsize=(10,10))
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()
```



ReLU + Adam Optimization + 5 Hidden Layers (without Dropout

and Batch Normalization)

Hidden layer 1 consists of 512 outputs and Hidden Layer2 consists of 256 outputs, Hidden Layer 3 consists of 128 outputs ,Hidden Layer 4 consists of 64 outputs,Hidden Layer 5 consists of 32 outputs

In [106]:

```
# Multilayer perceptron

model_relu = Sequential() #says we want a sequential model
model_relu.add(Dense(512, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNor
mal(mean=0.0, stddev=0.062, seed=None)))
model_relu.add(Dense(256, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.125
, seed=None)) )
model_relu.add(Dense(128, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.125
, seed=None)) )
model_relu.add(Dense(64, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.125,
seed=None)) )
model_relu.add(Dense(32, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.125,
seed=None)) )
model_relu.add(Dense(output_dim, activation='softmax'))

model_relu.summary()#prints the summary
```

```
Model: "sequential_18"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_66 (Dense)             (None, 512)               401920
_________________________________________________________________
dense_67 (Dense)             (None, 256)               131328
_________________________________________________________________
dense_68 (Dense)             (None, 128)               32896
_________________________________________________________________
dense_69 (Dense)             (None, 64)                8256
_________________________________________________________________
dense_70 (Dense)             (None, 32)                2080
_________________________________________________________________
dense_71 (Dense)             (None, 10)                330
=================================================================
Total params: 576,810
Trainable params: 576,810
Non-trainable params: 0
_________________________________________________________________
```

In [107]:

```
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))
```

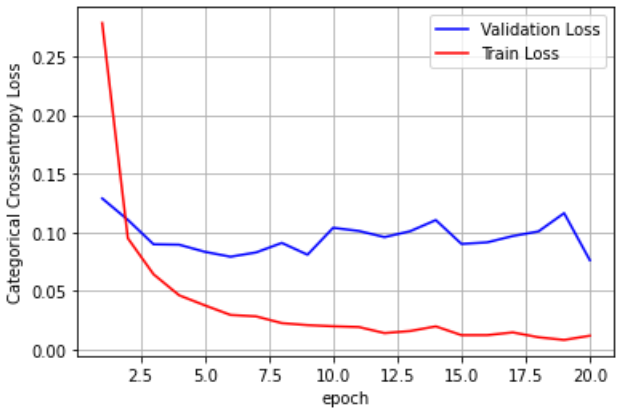
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 8s 130us/step - loss: 0.2782 - accuracy: 0.9158 - v
al_loss: 0.1288 - val_accuracy: 0.9611
Epoch 2/20
60000/60000 [==============================] - 8s 127us/step - loss: 0.0949 - accuracy: 0.9704 - v
al_loss: 0.1105 - val_accuracy: 0.9667
Epoch 3/20
60000/60000 [==============================] - 8s 127us/step - loss: 0.0642 - accuracy: 0.9791 - v
al_loss: 0.0897 - val_accuracy: 0.9722
Epoch 4/20
60000/60000 [==============================] - 8s 125us/step - loss: 0.0463 - accuracy: 0.9853 - v
al_loss: 0.0894 - val_accuracy: 0.9732
Epoch 5/20
60000/60000 [==============================] - 8s 126us/step - loss: 0.0377 - accuracy: 0.9880 - v
al_loss: 0.0833 - val_accuracy: 0.9776
Epoch 6/20
60000/60000 [==============================] - 8s 126us/step - loss: 0.0296 - accuracy: 0.9906 - v
al_loss: 0.0791 - val_accuracy: 0.9789
```

```
Epoch 7/20
60000/60000 [==============================] - 8s 127us/step - loss: 0.0283 - accuracy: 0.9907 - v
al_loss: 0.0828 - val_accuracy: 0.9765
Epoch 8/20
60000/60000 [==============================] - 7s 125us/step - loss: 0.0226 - accuracy: 0.9925 - v
al_loss: 0.0909 - val_accuracy: 0.9756
Epoch 9/20
60000/60000 [==============================] - 7s 125us/step - loss: 0.0209 - accuracy: 0.9933 - v
al_loss: 0.0809 - val_accuracy: 0.9797
Epoch 10/20
60000/60000 [==============================] - 7s 124us/step - loss: 0.0199 - accuracy: 0.9936 - v
al_loss: 0.1038 - val_accuracy: 0.9758
Epoch 11/20
60000/60000 [==============================] - 7s 123us/step - loss: 0.0193 - accuracy: 0.9938 - v
al_loss: 0.1011 - val_accuracy: 0.9755
Epoch 12/20
60000/60000 [==============================] - 7s 123us/step - loss: 0.0141 - accuracy: 0.9953 - v
al_loss: 0.0958 - val_accuracy: 0.9781
Epoch 13/20
60000/60000 [==============================] - 7s 124us/step - loss: 0.0159 - accuracy: 0.9948 - v
al_loss: 0.1009 - val_accuracy: 0.9780
Epoch 14/20
60000/60000 [==============================] - 7s 124us/step - loss: 0.0198 - accuracy: 0.9940 - v
al_loss: 0.1104 - val_accuracy: 0.9759
Epoch 15/20
60000/60000 [==============================] - 7s 124us/step - loss: 0.0123 - accuracy: 0.9959 - v
al_loss: 0.0900 - val_accuracy: 0.9829
Epoch 16/20
60000/60000 [==============================] - 7s 123us/step - loss: 0.0124 - accuracy: 0.9961 - v
al_loss: 0.0914 - val_accuracy: 0.9806
Epoch 17/20
60000/60000 [==============================] - 7s 123us/step - loss: 0.0147 - accuracy: 0.9952 - v
al_loss: 0.0968 - val_accuracy: 0.9795
Epoch 18/20
60000/60000 [==============================] - 7s 124us/step - loss: 0.0105 - accuracy: 0.9968 - v
al_loss: 0.1007 - val_accuracy: 0.9789
Epoch 19/20
60000/60000 [==============================] - 7s 125us/step - loss: 0.0083 - accuracy: 0.9974 - v
al_loss: 0.1163 - val_accuracy: 0.9785
Epoch 20/20
60000/60000 [==============================] - 7s 121us/step - loss: 0.0119 - accuracy: 0.9965 - v
al_loss: 0.0762 - val_accuracy: 0.9823
```

In [108]:

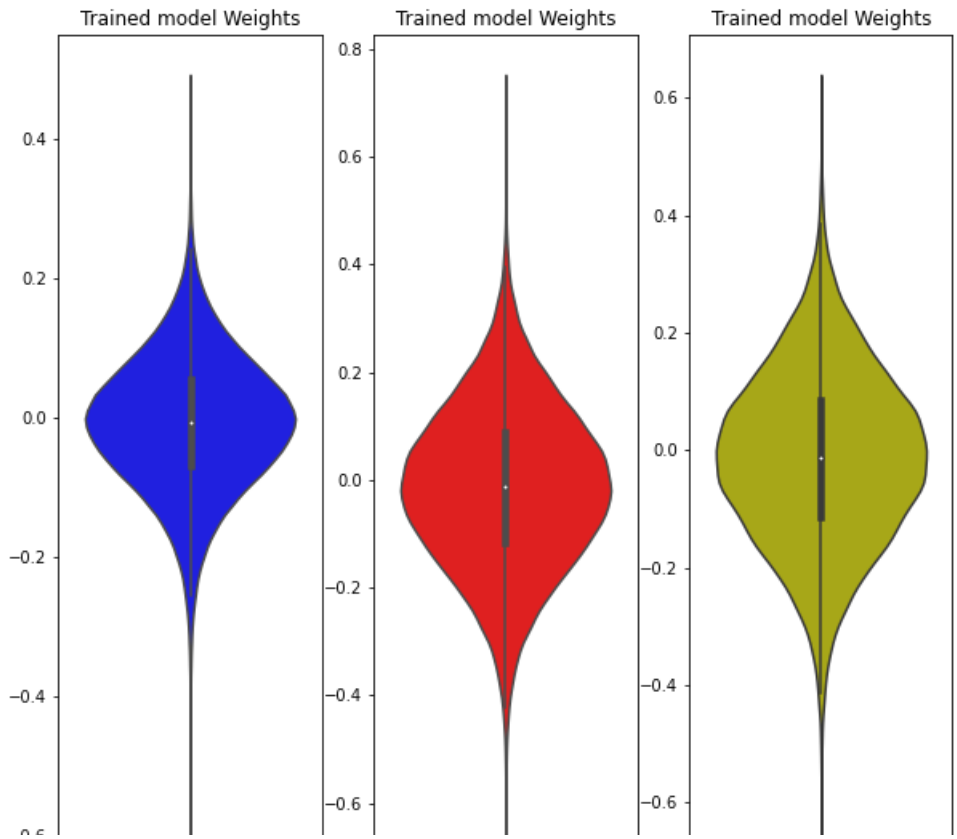
```
score = model_relu.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

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))

# print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, va
lidation_data=(X_test, Y_test))

# we will get val_loss and val_acc only when you pass the paramter validation_data
# val_loss : validation loss
# val_acc : validation accuracy

# loss : training loss
# acc : train accuracy
# for each key in histrory.histrory we will have a list of length equal to number of epochs


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

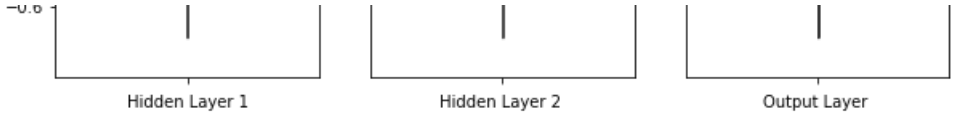
```
Test score: 0.07623335870537294
Test accuracy: 0.9822999835014343
```



In [109]:

```
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(figsize=(10,10))
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()
```





ReLU + Adam Optimization + 2 Hidden Layers (Batch Normalization)

In [110]:

```
from keras.layers.normalization import BatchNormalization

model_batch = Sequential()

model_batch.add(Dense(256, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNo
rmal(mean=0.0, stddev=0.039, seed=None)))
model_batch.add(BatchNormalization())

model_batch.add(Dense(64, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.55,
seed=None)) )
model_batch.add(BatchNormalization())

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


model_batch.summary()
```

```
Model: "sequential_19"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_72 (Dense)             (None, 256)               200960
_________________________________________________________________
batch_normalization_23 (Batc (None, 256)               1024
_________________________________________________________________
dense_73 (Dense)             (None, 64)                16448
_________________________________________________________________
batch_normalization_24 (Batc (None, 64)                256
_________________________________________________________________
dense_74 (Dense)             (None, 10)                650
=================================================================
Total params: 219,338
Trainable params: 218,698
Non-trainable params: 640
_________________________________________________________________
```

In [111]:

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

history = model_batch.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, vali
dation_data=(X_test, Y_test))
```

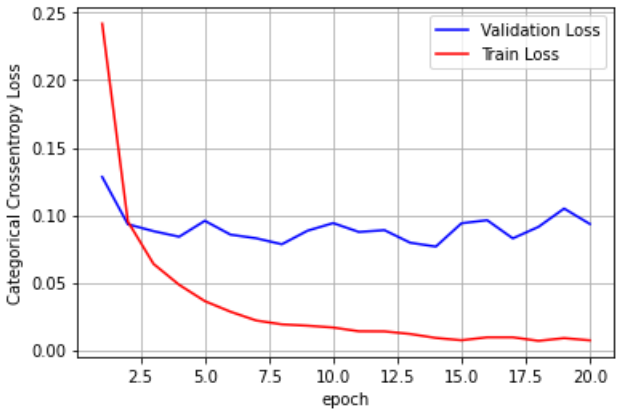
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 4s 68us/step - loss: 0.2419 - accuracy: 0.9304 - va
l_loss: 0.1283 - val_accuracy: 0.9619
Epoch 2/20
60000/60000 [==============================] - 4s 62us/step - loss: 0.0953 - accuracy: 0.9719 - va
l_loss: 0.0932 - val_accuracy: 0.9709
Epoch 3/20
60000/60000 [==============================] - 4s 62us/step - loss: 0.0639 - accuracy: 0.9810 - va
l_loss: 0.0881 - val_accuracy: 0.9730
Epoch 4/20
60000/60000 [==============================] - 4s 63us/step - loss: 0.0484 - accuracy: 0.9849 - va
l_loss: 0.0840 - val_accuracy: 0.9735
Epoch 5/20
60000/60000 [==============================] - 4s 61us/step - loss: 0.0363 - accuracy: 0.9890 - va
l_loss: 0.0958 - val_accuracy: 0.9703
Epoch 6/20
60000/60000 [==============================] - 4s 62us/step - loss: 0.0284 - accuracy: 0.9913 - va
```

```
l_loss: 0.0855 - val_accuracy: 0.9730
Epoch 7/20
60000/60000 [==============================] - 4s 61us/step - loss: 0.0219 - accuracy: 0.9933 - va
l_loss: 0.0829 - val_accuracy: 0.9753
Epoch 8/20
60000/60000 [==============================] - 4s 62us/step - loss: 0.0191 - accuracy: 0.9941 - va
l_loss: 0.0784 - val_accuracy: 0.9767
Epoch 9/20
60000/60000 [==============================] - 4s 63us/step - loss: 0.0181 - accuracy: 0.9943 - va
l_loss: 0.0885 - val_accuracy: 0.9748
Epoch 10/20
60000/60000 [==============================] - 4s 62us/step - loss: 0.0167 - accuracy: 0.9950 - va
l_loss: 0.0941 - val_accuracy: 0.9746
Epoch 11/20
60000/60000 [==============================] - 4s 62us/step - loss: 0.0140 - accuracy: 0.9956 - va
l_loss: 0.0875 - val_accuracy: 0.9748
Epoch 12/20
60000/60000 [==============================] - 4s 62us/step - loss: 0.0139 - accuracy: 0.9959 - va
l_loss: 0.0889 - val_accuracy: 0.9765
Epoch 13/20
60000/60000 [==============================] - 4s 62us/step - loss: 0.0120 - accuracy: 0.9962 - va
l_loss: 0.0796 - val_accuracy: 0.9796
Epoch 14/20
60000/60000 [==============================] - 4s 62us/step - loss: 0.0090 - accuracy: 0.9975 - va
l_loss: 0.0767 - val_accuracy: 0.9796
Epoch 15/20
60000/60000 [==============================] - 4s 62us/step - loss: 0.0073 - accuracy: 0.9979 - va
l_loss: 0.0940 - val_accuracy: 0.9764
Epoch 16/20
60000/60000 [==============================] - 4s 62us/step - loss: 0.0095 - accuracy: 0.9972 - va
l_loss: 0.0963 - val_accuracy: 0.9777
Epoch 17/20
60000/60000 [==============================] - 4s 62us/step - loss: 0.0095 - accuracy: 0.9973 - va
l_loss: 0.0828 - val_accuracy: 0.9787
Epoch 18/20
60000/60000 [==============================] - 4s 62us/step - loss: 0.0069 - accuracy: 0.9980 - va
l_loss: 0.0913 - val_accuracy: 0.9773
Epoch 19/20
60000/60000 [==============================] - 4s 61us/step - loss: 0.0089 - accuracy: 0.9971 - va
l_loss: 0.1049 - val_accuracy: 0.9735
Epoch 20/20
60000/60000 [==============================] - 4s 62us/step - loss: 0.0072 - accuracy: 0.9975 - va
l_loss: 0.0935 - val_accuracy: 0.9767
```

In [112]:

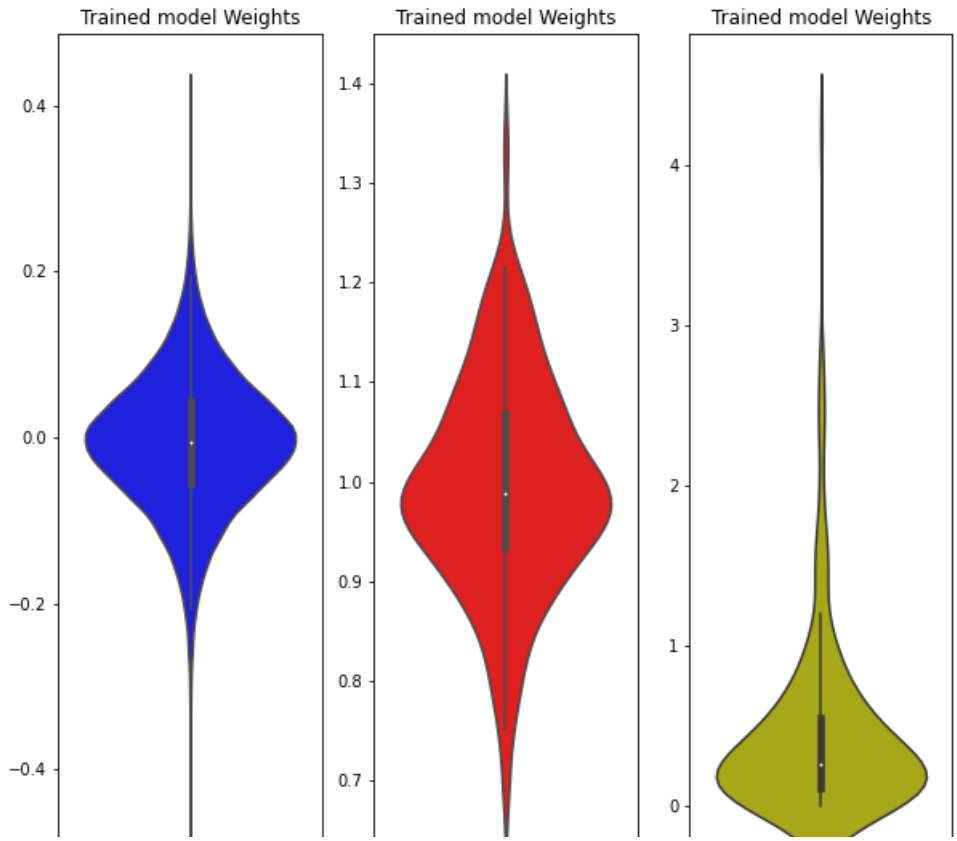
```
score = model_batch.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

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))

# print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, va
lidation_data=(X_test, Y_test))

# we will get val_loss and val_acc only when you pass the paramter validation_data
# val_loss : validation loss
# val_acc : validation accuracy

# loss : training loss
# acc : train accuracy
# for each key in histrory.histrory we will have a list of length equal to number of epochs

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

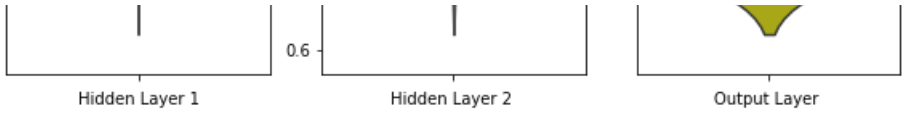
```
Test score: 0.09346026394422224
Test accuracy: 0.9767000079154968
```



In [113]:

```
w_after = model_batch.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(figsize=(10,10))
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()
```





ReLU + Adam Optimization + 3 Hidden Layers (Batch Normalization)

In [114]:

```
from keras.layers.normalization import BatchNormalization

model_batch = Sequential()

model_batch.add(Dense(512, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNo
rmal(mean=0.0, stddev=0.039, seed=None)))
model_batch.add(BatchNormalization())

model_batch.add(Dense(256, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.55
, seed=None)) )
model_batch.add(BatchNormalization())

model_batch.add(Dense(128, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.55
, seed=None)) )
model_batch.add(BatchNormalization())

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


model_batch.summary()
```

```
Model: "sequential_20"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_75 (Dense)             (None, 512)               401920
_________________________________________________________________
batch_normalization_25 (Batc (None, 512)               2048
_________________________________________________________________
dense_76 (Dense)             (None, 256)               131328
_________________________________________________________________
batch_normalization_26 (Batc (None, 256)               1024
_________________________________________________________________
dense_77 (Dense)             (None, 128)               32896
_________________________________________________________________
batch_normalization_27 (Batc (None, 128)               512
_________________________________________________________________
dense_78 (Dense)             (None, 10)                1290
=================================================================
Total params: 571,018
Trainable params: 569,226
Non-trainable params: 1,792
_________________________________________________________________
```

In [115]:

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

history = model_batch.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, vali
dation_data=(X_test, Y_test))
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 9s 148us/step - loss: 0.2114 - accuracy: 0.9378 - v
al_loss: 0.1119 - val_accuracy: 0.9654
Epoch 2/20
60000/60000 [==============================] - 9s 142us/step - loss: 0.0754 - accuracy: 0.9776 - v
al_loss: 0.0913 - val_accuracy: 0.9715
Epoch 3/20
60000/60000 [==============================] - 8s 141us/step - loss: 0.0473 - accuracy: 0.9857 - v
al_loss: 0.0888 - val_accuracy: 0.9721
```

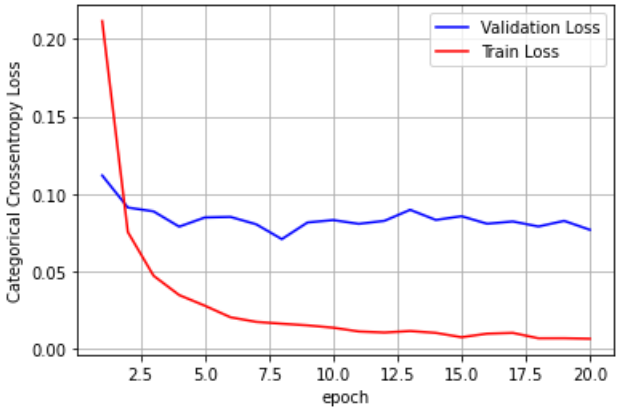
```
Epoch 4/20
60000/60000 [==============================] - 9s 143us/step - loss: 0.0349 - accuracy: 0.9884 - v
al_loss: 0.0789 - val_accuracy: 0.9750
Epoch 5/20
60000/60000 [==============================] - 8s 141us/step - loss: 0.0280 - accuracy: 0.9912 - v
al_loss: 0.0849 - val_accuracy: 0.9740
Epoch 6/20
60000/60000 [==============================] - 9s 142us/step - loss: 0.0206 - accuracy: 0.9934 - v
al_loss: 0.0852 - val_accuracy: 0.9756
Epoch 7/20
60000/60000 [==============================] - 8s 141us/step - loss: 0.0176 - accuracy: 0.9942 - v
al_loss: 0.0805 - val_accuracy: 0.9767
Epoch 8/20
60000/60000 [==============================] - 8s 141us/step - loss: 0.0164 - accuracy: 0.9945 - v
al_loss: 0.0709 - val_accuracy: 0.9791
Epoch 9/20
60000/60000 [==============================] - 9s 142us/step - loss: 0.0153 - accuracy: 0.9948 - v
al_loss: 0.0816 - val_accuracy: 0.9769
Epoch 10/20
60000/60000 [==============================] - 9s 144us/step - loss: 0.0138 - accuracy: 0.9955 - v
al_loss: 0.0832 - val_accuracy: 0.9765
Epoch 11/20
60000/60000 [==============================] - 9s 148us/step - loss: 0.0114 - accuracy: 0.9961 - v
al_loss: 0.0807 - val_accuracy: 0.9767
Epoch 12/20
60000/60000 [==============================] - 9s 151us/step - loss: 0.0107 - accuracy: 0.9964 - v
al_loss: 0.0827 - val_accuracy: 0.9774
Epoch 13/20
60000/60000 [==============================] - 9s 145us/step - loss: 0.0117 - accuracy: 0.9961 - v
al_loss: 0.0898 - val_accuracy: 0.9793
Epoch 14/20
60000/60000 [==============================] - 9s 144us/step - loss: 0.0105 - accuracy: 0.9968 - v
al_loss: 0.0833 - val_accuracy: 0.9792
Epoch 15/20
60000/60000 [==============================] - 9s 144us/step - loss: 0.0077 - accuracy: 0.9974 - v
al_loss: 0.0857 - val_accuracy: 0.9790
Epoch 16/20
60000/60000 [==============================] - 9s 146us/step - loss: 0.0100 - accuracy: 0.9965 - v
al_loss: 0.0808 - val_accuracy: 0.9809
Epoch 17/20
60000/60000 [==============================] - 9s 144us/step - loss: 0.0105 - accuracy: 0.9966 - v
al_loss: 0.0823 - val_accuracy: 0.9813
Epoch 18/20
60000/60000 [==============================] - 9s 144us/step - loss: 0.0070 - accuracy: 0.9975 - v
al_loss: 0.0790 - val_accuracy: 0.9809
Epoch 19/20
60000/60000 [==============================] - 9s 143us/step - loss: 0.0070 - accuracy: 0.9977 - v
al_loss: 0.0827 - val_accuracy: 0.9776
Epoch 20/20
60000/60000 [==============================] - 9s 146us/step - loss: 0.0067 - accuracy: 0.9978 - v
al_loss: 0.0769 - val_accuracy: 0.9819
```

In [116]:

```
score = model_batch.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))

# print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, va
lidation_data=(X_test, Y_test))

# we will get val_loss and val_acc only when you pass the paramter validation_data
# val_loss : validation loss
# val_acc : validation accuracy

# loss : training loss
# acc : train accuracy
# for each key in histrory.histrory we will have a list of length equal to number of epochs
```

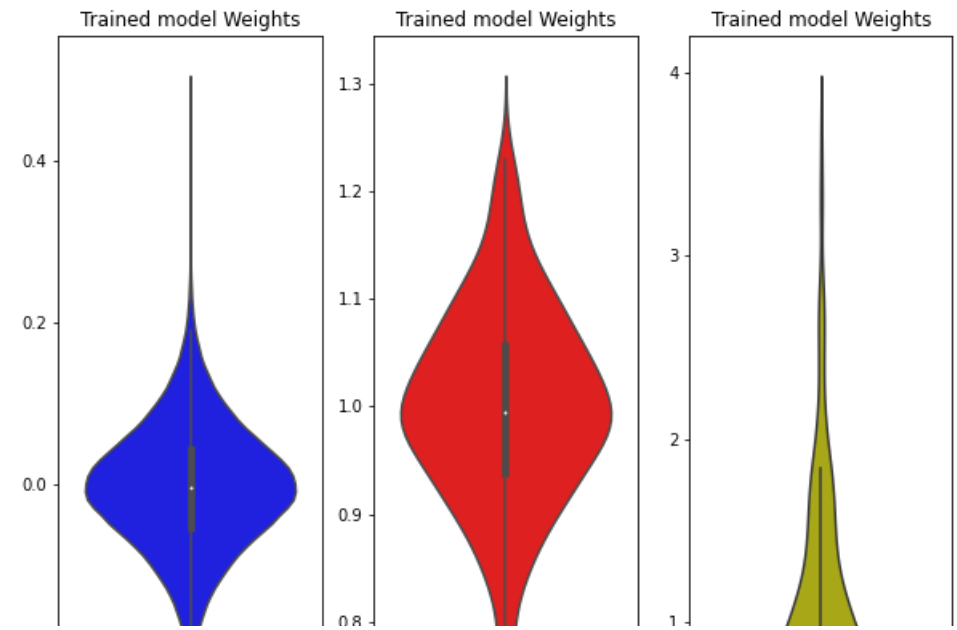
```
vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
```

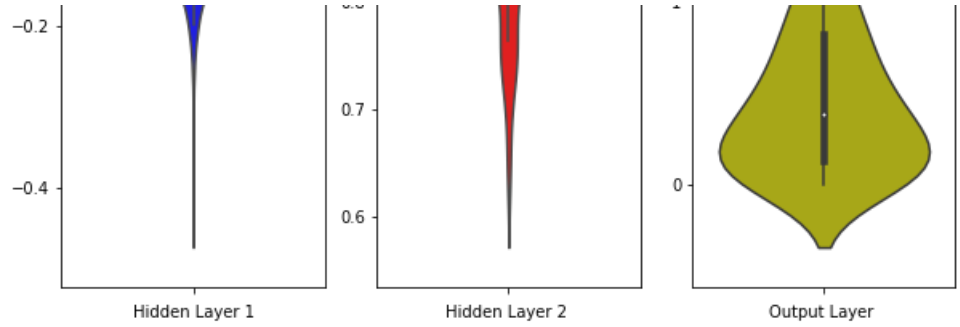
```
Test score: 0.07694103825540023
Test accuracy: 0.9818999767303467
```



In [117]:

```
w_after = model_batch.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(figsize=(10,10))
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()
```





ReLU + Adam Optimization + 5 Hidden Layers (Batch Normalization)

In [118]:

```
from keras.layers.normalization import BatchNormalization

model_batch = Sequential()

model_batch.add(Dense(512, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNo
rmal(mean=0.0, stddev=0.039, seed=None)))
model_batch.add(BatchNormalization())

model_batch.add(Dense(256, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.55
, seed=None)) )
model_batch.add(BatchNormalization())

model_batch.add(Dense(128, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.55
, seed=None)) )
model_batch.add(BatchNormalization())

model_batch.add(Dense(64, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.55,
seed=None)) )
model_batch.add(BatchNormalization())

model_batch.add(Dense(32, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.55,
seed=None)) )
model_batch.add(BatchNormalization())

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


model_batch.summary()
```

```
Model: "sequential_21"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_79 (Dense)             (None, 512)               401920
_________________________________________________________________
batch_normalization_28 (Batc (None, 512)               2048
_________________________________________________________________
dense_80 (Dense)             (None, 256)               131328
_________________________________________________________________
batch_normalization_29 (Batc (None, 256)               1024
_________________________________________________________________
dense_81 (Dense)             (None, 128)               32896
_________________________________________________________________
batch_normalization_30 (Batc (None, 128)               512
_________________________________________________________________
dense_82 (Dense)             (None, 64)                8256
_________________________________________________________________
batch_normalization_31 (Batc (None, 64)                256
_________________________________________________________________
dense_83 (Dense)             (None, 32)                2080
_________________________________________________________________
batch_normalization_32 (Batc (None, 32)                128
_________________________________________________________________
dense_84 (Dense)             (None, 10)                330
=================================================================
```

```
Total params: 580,778
Trainable params: 578,794
Non-trainable params: 1,984
_________________________________________________________________
```

In [119]:

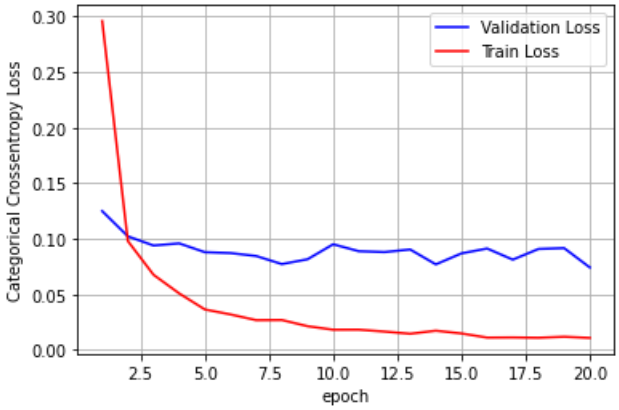
```
model_batch.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history = model_batch.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, vali
dation_data=(X_test, Y_test))
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 10s 166us/step - loss: 0.2957 - accuracy: 0.9186 -
val_loss: 0.1249 - val_accuracy: 0.9658
Epoch 2/20
60000/60000 [==============================] - 9s 152us/step - loss: 0.0979 - accuracy: 0.9710 - v
al_loss: 0.1022 - val_accuracy: 0.9691
Epoch 3/20
60000/60000 [==============================] - 9s 152us/step - loss: 0.0676 - accuracy: 0.9790 - v
al_loss: 0.0939 - val_accuracy: 0.9710
Epoch 4/20
60000/60000 [==============================] - 9s 153us/step - loss: 0.0509 - accuracy: 0.9843 - v
al_loss: 0.0959 - val_accuracy: 0.9682
Epoch 5/20
60000/60000 [==============================] - 9s 153us/step - loss: 0.0365 - accuracy: 0.9881 - v
al_loss: 0.0879 - val_accuracy: 0.9741
Epoch 6/20
60000/60000 [==============================] - 9s 151us/step - loss: 0.0320 - accuracy: 0.9897 - v
al_loss: 0.0871 - val_accuracy: 0.9760
Epoch 7/20
60000/60000 [==============================] - 9s 153us/step - loss: 0.0268 - accuracy: 0.9916 - v
al_loss: 0.0845 - val_accuracy: 0.9756
Epoch 8/20
60000/60000 [==============================] - 9s 154us/step - loss: 0.0270 - accuracy: 0.9910 - v
al_loss: 0.0773 - val_accuracy: 0.9787
Epoch 9/20
60000/60000 [==============================] - 9s 153us/step - loss: 0.0214 - accuracy: 0.9930 - v
al_loss: 0.0816 - val_accuracy: 0.9771
Epoch 10/20
60000/60000 [==============================] - 9s 153us/step - loss: 0.0183 - accuracy: 0.9940 - v
al_loss: 0.0951 - val_accuracy: 0.9723
Epoch 11/20
60000/60000 [==============================] - 9s 155us/step - loss: 0.0183 - accuracy: 0.9936 - v
al_loss: 0.0888 - val_accuracy: 0.9754
Epoch 12/20
60000/60000 [==============================] - 9s 154us/step - loss: 0.0166 - accuracy: 0.9944 - v
al_loss: 0.0880 - val_accuracy: 0.9768
Epoch 13/20
60000/60000 [==============================] - 9s 152us/step - loss: 0.0146 - accuracy: 0.9954 - v
al_loss: 0.0904 - val_accuracy: 0.9759
Epoch 14/20
60000/60000 [==============================] - 9s 155us/step - loss: 0.0174 - accuracy: 0.9944 - v
al_loss: 0.0770 - val_accuracy: 0.9795
Epoch 15/20
60000/60000 [==============================] - 9s 151us/step - loss: 0.0149 - accuracy: 0.9951 - v
al_loss: 0.0869 - val_accuracy: 0.9779
Epoch 16/20
60000/60000 [==============================] - 9s 155us/step - loss: 0.0112 - accuracy: 0.9964 - v
al_loss: 0.0912 - val_accuracy: 0.9780
Epoch 17/20
60000/60000 [==============================] - 10s 160us/step - loss: 0.0113 - accuracy: 0.9961 -
val_loss: 0.0812 - val_accuracy: 0.9808
Epoch 18/20
60000/60000 [==============================] - 9s 153us/step - loss: 0.0110 - accuracy: 0.9963 - v
al_loss: 0.0908 - val_accuracy: 0.9785
Epoch 19/20
60000/60000 [==============================] - 9s 153us/step - loss: 0.0119 - accuracy: 0.9962 - v
al_loss: 0.0916 - val_accuracy: 0.9802
Epoch 20/20
60000/60000 [==============================] - 9s 151us/step - loss: 0.0109 - accuracy: 0.9964 - v
al_loss: 0.0742 - val_accuracy: 0.9815
```

In [120]:

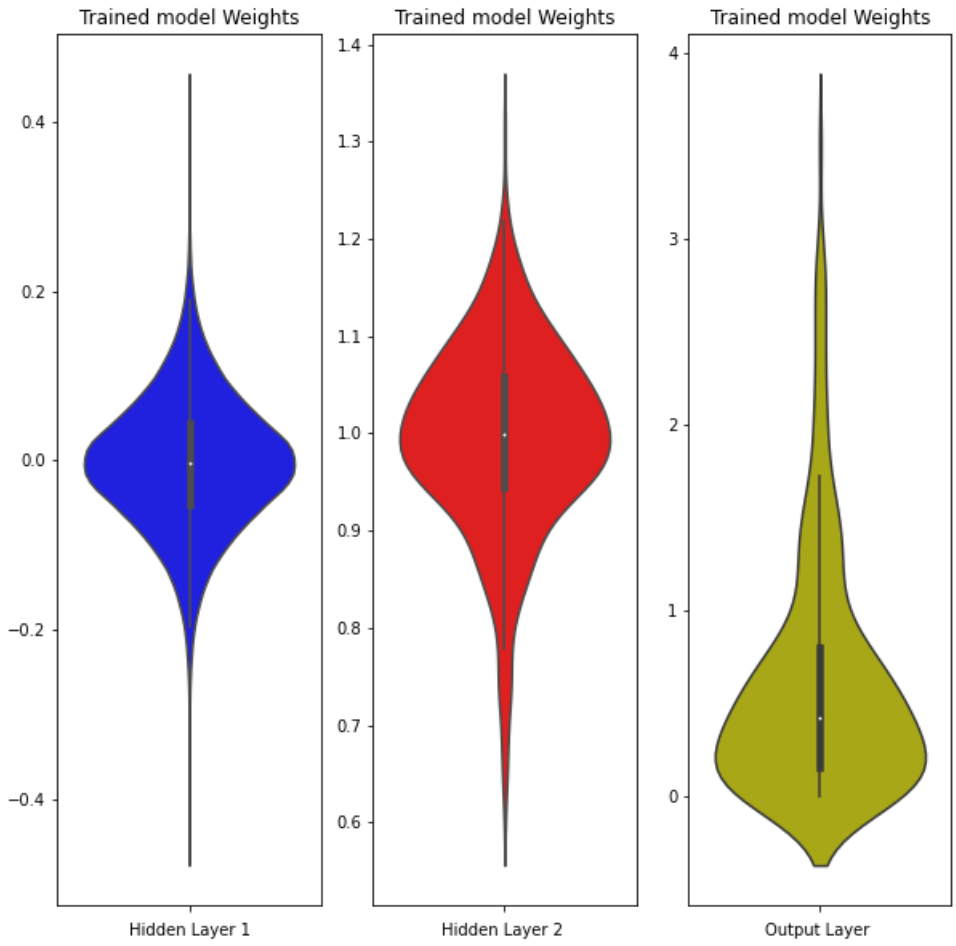
```
score = model_batch.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

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))

# print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, va
lidation_data=(X_test, Y_test))

# we will get val_loss and val_acc only when you pass the paramter validation_data
# val_loss : validation loss
# val_acc : validation accuracy

# loss : training loss
# acc : train accuracy
# for each key in histrory.histrory we will have a list of length equal to number of epochs

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

```
Test score: 0.07422380950862426
Test accuracy: 0.9815000295639038
```



In [121]:

```
w_after = model_batch.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(figsize=(10,10))
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()
```



ReLU + Adam Optimization + 2 Hidden Layers (with Dropout and Batch Normalization)

In [122]:

```
# https://stackoverflow.com/questions/34716454/where-do-i-call-the-batchnormalization-function-in-keras

from keras.layers import Dropout

model_drop = Sequential()

model_drop.add(Dense(256, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNormal(mean=0.0, stddev=0.039, seed=None)))
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

model_drop.add(Dense(64, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.55, seed=None)) )
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

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


model_drop.summary()
```

```
Model: "sequential_22"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_85 (Dense)             (None, 256)               200960
_________________________________________________________________
batch_normalization_33 (Batc (None, 256)               1024
```

```
_________________________________________________________________
dropout_11 (Dropout)         (None, 256)               0
_________________________________________________________________
dense_86 (Dense)             (None, 64)                16448
_________________________________________________________________
batch_normalization_34 (Batc (None, 64)                256
_________________________________________________________________
dropout_12 (Dropout)         (None, 64)                0
_________________________________________________________________
dense_87 (Dense)             (None, 10)                650
=================================================================
Total params: 219,338
Trainable params: 218,698
Non-trainable params: 640
_________________________________________________________________
```

In [123]:

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

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

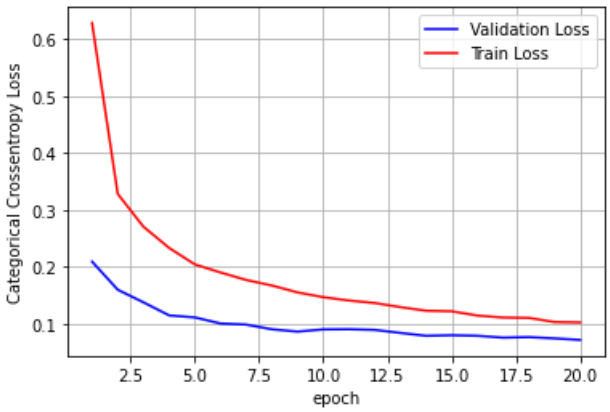
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 5s 76us/step - loss: 0.6283 - accuracy: 0.8107 - va
l_loss: 0.2089 - val_accuracy: 0.9392
Epoch 2/20
60000/60000 [==============================] - 4s 71us/step - loss: 0.3279 - accuracy: 0.9043 - va
l_loss: 0.1595 - val_accuracy: 0.9493
Epoch 3/20
60000/60000 [==============================] - 4s 70us/step - loss: 0.2703 - accuracy: 0.9201 - va
l_loss: 0.1373 - val_accuracy: 0.9561
Epoch 4/20
60000/60000 [==============================] - 4s 70us/step - loss: 0.2330 - accuracy: 0.9319 - va
l_loss: 0.1144 - val_accuracy: 0.9645
Epoch 5/20
60000/60000 [==============================] - 4s 70us/step - loss: 0.2040 - accuracy: 0.9405 - va
l_loss: 0.1108 - val_accuracy: 0.9649
Epoch 6/20
60000/60000 [==============================] - 4s 70us/step - loss: 0.1898 - accuracy: 0.9439 - va
l_loss: 0.1002 - val_accuracy: 0.9708
Epoch 7/20
60000/60000 [==============================] - 4s 71us/step - loss: 0.1766 - accuracy: 0.9481 - va
l_loss: 0.0982 - val_accuracy: 0.9711
Epoch 8/20
60000/60000 [==============================] - 4s 71us/step - loss: 0.1669 - accuracy: 0.9509 - va
l_loss: 0.0899 - val_accuracy: 0.9727
Epoch 9/20
60000/60000 [==============================] - 4s 70us/step - loss: 0.1548 - accuracy: 0.9549 - va
l_loss: 0.0859 - val_accuracy: 0.9743
Epoch 10/20
60000/60000 [==============================] - 4s 69us/step - loss: 0.1464 - accuracy: 0.9570 - va
l_loss: 0.0898 - val_accuracy: 0.9731
Epoch 11/20
60000/60000 [==============================] - 4s 69us/step - loss: 0.1405 - accuracy: 0.9590 - va
l_loss: 0.0900 - val_accuracy: 0.9749
Epoch 12/20
60000/60000 [==============================] - 4s 69us/step - loss: 0.1362 - accuracy: 0.9589 - va
l_loss: 0.0889 - val_accuracy: 0.9746
Epoch 13/20
60000/60000 [==============================] - 4s 70us/step - loss: 0.1289 - accuracy: 0.9618 - va
l_loss: 0.0836 - val_accuracy: 0.9749
Epoch 14/20
60000/60000 [==============================] - 4s 72us/step - loss: 0.1225 - accuracy: 0.9635 - va
l_loss: 0.0785 - val_accuracy: 0.9776
Epoch 15/20
60000/60000 [==============================] - 4s 70us/step - loss: 0.1216 - accuracy: 0.9641 - va
l_loss: 0.0795 - val_accuracy: 0.9771
Epoch 16/20
60000/60000 [==============================] - 4s 70us/step - loss: 0.1141 - accuracy: 0.9664 - va
l_loss: 0.0785 - val_accuracy: 0.9785
Epoch 17/20
60000/60000 [==============================] - 4s 70us/step - loss: 0.1106 - accuracy: 0.9674 - va
l_loss: 0.0753 - val_accuracy: 0.9779
Epoch 18/20
```

```
60000/60000 [==============================] - 4s 71us/step - loss: 0.1100 - accuracy: 0.9667 - va
l_loss: 0.0762 - val_accuracy: 0.9786
Epoch 19/20
60000/60000 [==============================] - 4s 71us/step - loss: 0.1027 - accuracy: 0.9696 - va
l_loss: 0.0739 - val_accuracy: 0.9789
Epoch 20/20
60000/60000 [==============================] - 4s 70us/step - loss: 0.1020 - accuracy: 0.9692 - va
l_loss: 0.0713 - val_accuracy: 0.9795
```

In [124]:

```
score = model_drop.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))

# print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, va
lidation_data=(X_test, Y_test))

# we will get val_loss and val_acc only when you pass the paramter validation_data
# val_loss : validation loss
# val_acc : validation accuracy

# loss : training loss
# acc : train accuracy
# for each key in histrory.histrory we will have a list of length equal to number of epochs

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

```
Test score: 0.0712568270204123
Test accuracy: 0.9794999957084656
```

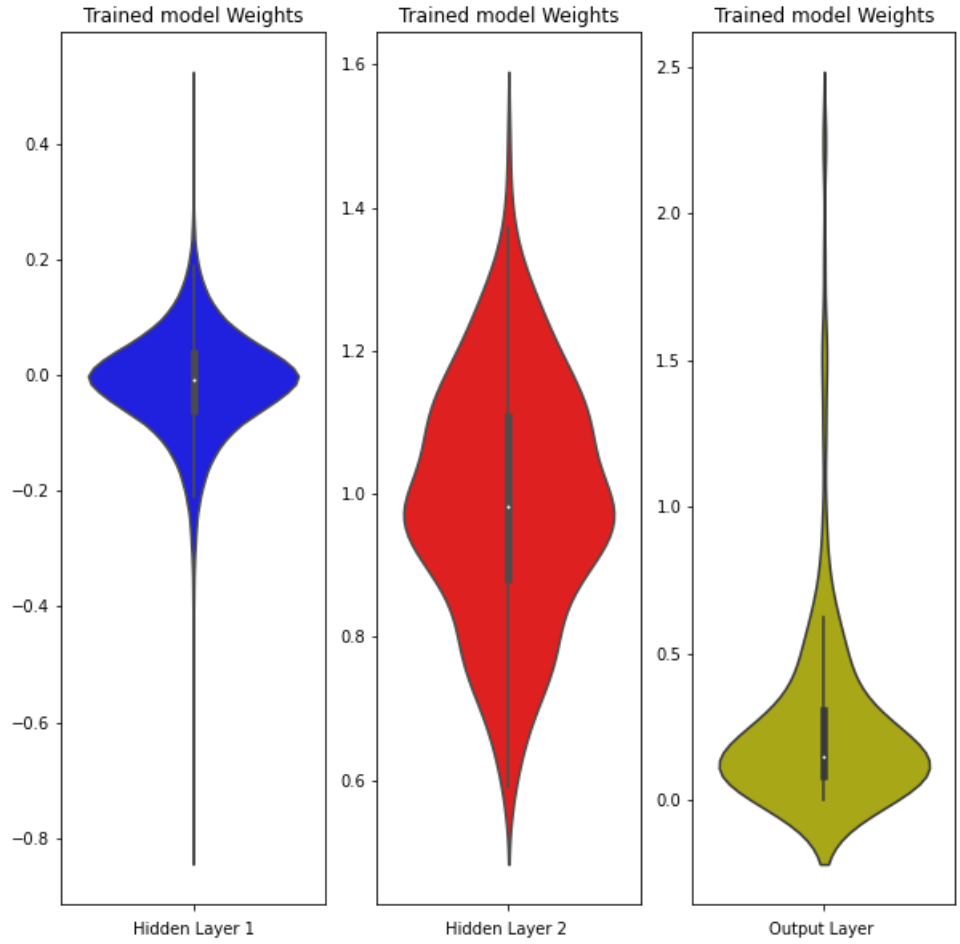


both training and validation loss keeps on decreasing with the increase in no of epochs and around 20epochs both the losses are pretty similar or almost the same

In [125]:

```
w_after = model_drop.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(figsize=(10,10))
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()
```



ReLU + Adam Optimization + 3 Hidden Layers (with Dropout and Batch Normalization)

In [126]:

```
# https://stackoverflow.com/questions/34716454/where-do-i-call-the-batchnormalization-function-in-keras

from keras.layers import Dropout

model_drop = Sequential()

model_drop.add(Dense(512, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNormal(mean=0.0, stddev=0.039, seed=None)))
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

model_drop.add(Dense(256, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.55, seed=None)) )
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))
```

```
model_drop.add(Dense(128, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.55,
seed=None)) )
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

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


model_drop.summary()
```

```
Model: "sequential_23"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_88 (Dense)             (None, 512)               401920
_________________________________________________________________
batch_normalization_35 (Batc (None, 512)               2048
_________________________________________________________________
dropout_13 (Dropout)         (None, 512)               0
_________________________________________________________________
dense_89 (Dense)             (None, 256)               131328
_________________________________________________________________
batch_normalization_36 (Batc (None, 256)               1024
_________________________________________________________________
dropout_14 (Dropout)         (None, 256)               0
_________________________________________________________________
dense_90 (Dense)             (None, 128)               32896
_________________________________________________________________
batch_normalization_37 (Batc (None, 128)               512
_________________________________________________________________
dropout_15 (Dropout)         (None, 128)               0
_________________________________________________________________
dense_91 (Dense)             (None, 10)                1290
=================================================================
Total params: 571,018
Trainable params: 569,226
Non-trainable params: 1,792
_________________________________________________________________
```

In [127]:

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

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

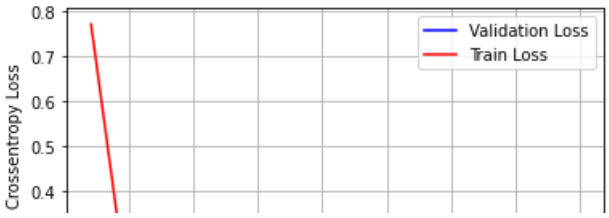
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 10s 163us/step - loss: 0.7715 - accuracy: 0.7613 -
val_loss: 0.2116 - val_accuracy: 0.9358
Epoch 2/20
60000/60000 [==============================] - 9s 155us/step - loss: 0.3486 - accuracy: 0.8948 - v
al_loss: 0.1556 - val_accuracy: 0.9508
Epoch 3/20
60000/60000 [==============================] - 10s 163us/step - loss: 0.2721 - accuracy: 0.9203 -
val_loss: 0.1334 - val_accuracy: 0.9579
Epoch 4/20
60000/60000 [==============================] - 10s 159us/step - loss: 0.2331 - accuracy: 0.9324 -
val_loss: 0.1208 - val_accuracy: 0.9618
Epoch 5/20
60000/60000 [==============================] - 9s 153us/step - loss: 0.2010 - accuracy: 0.9418 - v
al_loss: 0.1079 - val_accuracy: 0.9667
Epoch 6/20
60000/60000 [==============================] - 9s 154us/step - loss: 0.1785 - accuracy: 0.9483 - v
al_loss: 0.0947 - val_accuracy: 0.9722
Epoch 7/20
60000/60000 [==============================] - 9s 155us/step - loss: 0.1664 - accuracy: 0.9522 - v
al_loss: 0.0903 - val_accuracy: 0.9724
Epoch 8/20
60000/60000 [==============================] - 9s 154us/step - loss: 0.1541 - accuracy: 0.9549 - v
al_loss: 0.0878 - val_accuracy: 0.9734
Epoch 9/20
60000/60000 [==============================] - 9s 155us/step - loss: 0.1464 - accuracy: 0.9574 - v
```

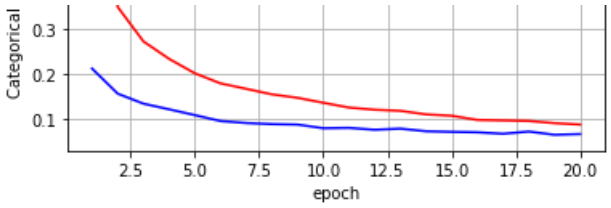
```
al_loss: 0.0868 - val_accuracy: 0.9733
Epoch 10/20
60000/60000 [==============================] - 9s 155us/step - loss: 0.1354 - accuracy: 0.9606 - v
al_loss: 0.0787 - val_accuracy: 0.9751
Epoch 11/20
60000/60000 [==============================] - 9s 156us/step - loss: 0.1247 - accuracy: 0.9627 - v
al_loss: 0.0794 - val_accuracy: 0.9764
Epoch 12/20
60000/60000 [==============================] - 9s 153us/step - loss: 0.1199 - accuracy: 0.9639 - v
al_loss: 0.0752 - val_accuracy: 0.9782
Epoch 13/20
60000/60000 [==============================] - 9s 156us/step - loss: 0.1174 - accuracy: 0.9660 - v
al_loss: 0.0777 - val_accuracy: 0.9780
Epoch 14/20
60000/60000 [==============================] - 9s 154us/step - loss: 0.1095 - accuracy: 0.9674 - v
al_loss: 0.0719 - val_accuracy: 0.9781
Epoch 15/20
60000/60000 [==============================] - 9s 156us/step - loss: 0.1065 - accuracy: 0.9680 - v
al_loss: 0.0706 - val_accuracy: 0.9784
Epoch 16/20
60000/60000 [==============================] - 9s 154us/step - loss: 0.0971 - accuracy: 0.9708 - v
al_loss: 0.0696 - val_accuracy: 0.9807
Epoch 17/20
60000/60000 [==============================] - 9s 154us/step - loss: 0.0960 - accuracy: 0.9717 - v
al_loss: 0.0663 - val_accuracy: 0.9814
Epoch 18/20
60000/60000 [==============================] - 9s 155us/step - loss: 0.0948 - accuracy: 0.9719 - v
al_loss: 0.0713 - val_accuracy: 0.9797
Epoch 19/20
60000/60000 [==============================] - 9s 155us/step - loss: 0.0900 - accuracy: 0.9731 - v
al_loss: 0.0641 - val_accuracy: 0.9831
Epoch 20/20
60000/60000 [==============================] - 9s 154us/step - loss: 0.0869 - accuracy: 0.9742 - v
al_loss: 0.0657 - val_accuracy: 0.9818
```

In [128]:

```
score = model_drop.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))

# print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, va
lidation_data=(X_test, Y_test))

# we will get val_loss and val_acc only when you pass the paramter validation_data
# val_loss : validation loss
# val_acc : validation accuracy

# loss : training loss
# acc : train accuracy
# for each key in histrory.histrory we will have a list of length equal to number of epochs

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

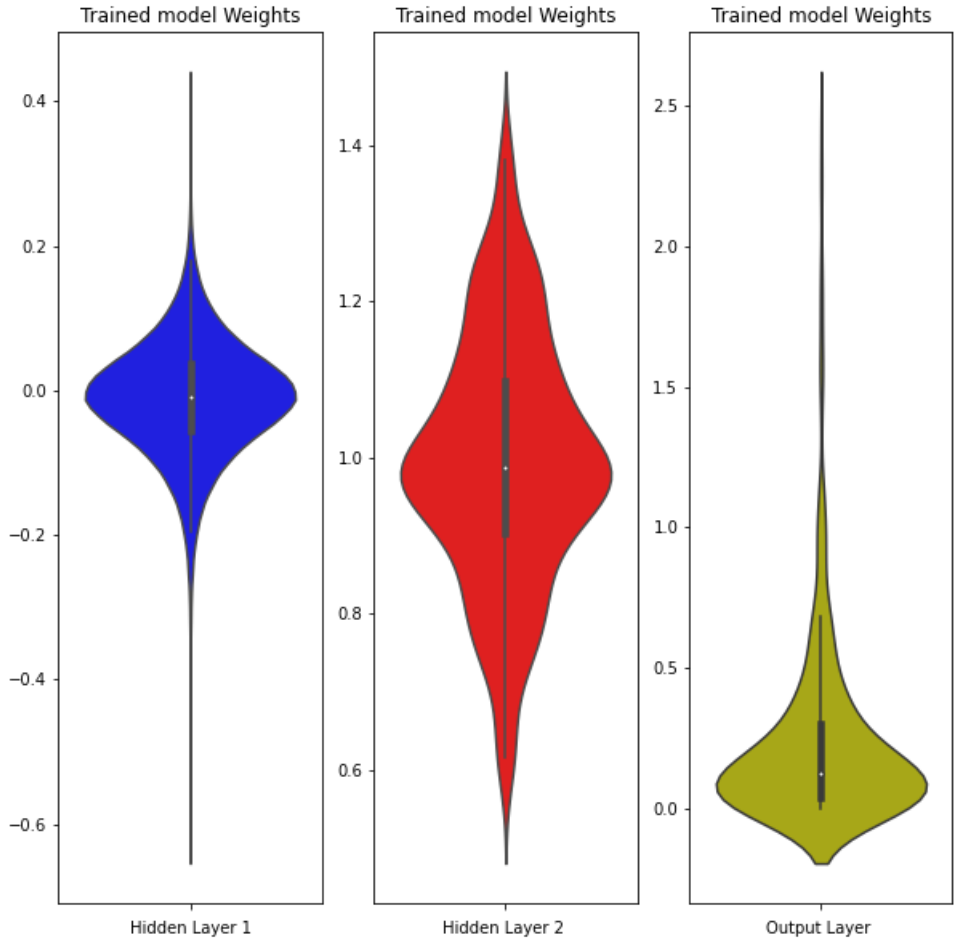
```
Test score: 0.06569366658385843
Test accuracy: 0.9818000197410583
```





In [129]:

```
w_after = model_drop.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(figsize=(10,10))
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()
```



ReLU + Adam Optimization + 5 Hidden Layers (with Dropout and

ReLU + Adam Optimization + 5 Hidden Layers (with Dropout and Batch Normalization)

In [130]:

```
# https://stackoverflow.com/questions/34716454/where-do-i-call-the-batchnormalization-function-in-keras

from keras.layers import Dropout

model_drop = Sequential()

model_drop.add(Dense(512, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNormal(mean=0.0, stddev=0.039, seed=None)))
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

model_drop.add(Dense(256, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.55, seed=None)) )
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

model_drop.add(Dense(128, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.55, seed=None)) )
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

model_drop.add(Dense(64, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.55, seed=None)) )
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

model_drop.add(Dense(32, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.55, seed=None)) )
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

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


model_drop.summary()
```

```
Model: "sequential_24"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_92 (Dense)             (None, 512)               401920
_________________________________________________________________
batch_normalization_38 (Batc (None, 512)               2048
_________________________________________________________________
dropout_16 (Dropout)         (None, 512)               0
_________________________________________________________________
dense_93 (Dense)             (None, 256)               131328
_________________________________________________________________
batch_normalization_39 (Batc (None, 256)               1024
_________________________________________________________________
dropout_17 (Dropout)         (None, 256)               0
_________________________________________________________________
dense_94 (Dense)             (None, 128)               32896
_________________________________________________________________
batch_normalization_40 (Batc (None, 128)               512
_________________________________________________________________
dropout_18 (Dropout)         (None, 128)               0
_________________________________________________________________
dense_95 (Dense)             (None, 64)                8256
_________________________________________________________________
batch_normalization_41 (Batc (None, 64)                256
_________________________________________________________________
dropout_19 (Dropout)         (None, 64)                0
_________________________________________________________________
dense_96 (Dense)             (None, 32)                2080
_________________________________________________________________
batch_normalization_42 (Batc (None, 32)                128
_________________________________________________________________
dropout_20 (Dropout)         (None, 32)                0
```

```
_________________________________________________________________
dense_97 (Dense)             (None, 10)                330       
=================================================================
Total params: 580,778
Trainable params: 578,794
Non-trainable params: 1,984
_________________________________________________________________
```

In [131]:

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

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

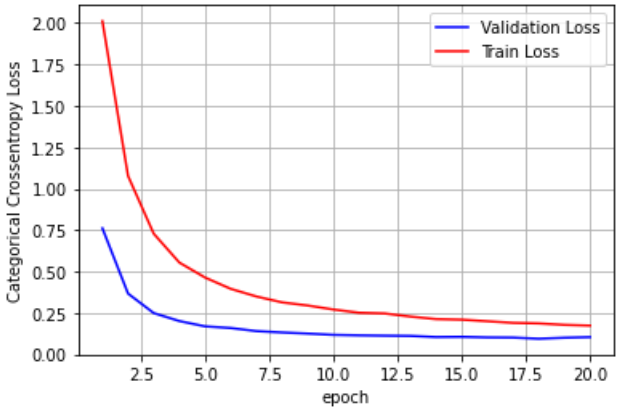
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 11s 186us/step - loss: 2.0119 - accuracy: 0.3304 -
val_loss: 0.7607 - val_accuracy: 0.8444
Epoch 2/20
60000/60000 [==============================] - 10s 166us/step - loss: 1.0764 - accuracy: 0.6406 -
val_loss: 0.3660 - val_accuracy: 0.9143
Epoch 3/20
60000/60000 [==============================] - 10s 166us/step - loss: 0.7278 - accuracy: 0.7714 -
val_loss: 0.2483 - val_accuracy: 0.9346
Epoch 4/20
60000/60000 [==============================] - 10s 166us/step - loss: 0.5533 - accuracy: 0.8357 -
val_loss: 0.2000 - val_accuracy: 0.9451
Epoch 5/20
60000/60000 [==============================] - 10s 165us/step - loss: 0.4630 - accuracy: 0.8702 -
val_loss: 0.1681 - val_accuracy: 0.9537
Epoch 6/20
60000/60000 [==============================] - 10s 165us/step - loss: 0.3948 - accuracy: 0.8964 -
val_loss: 0.1581 - val_accuracy: 0.9583
Epoch 7/20
60000/60000 [==============================] - 10s 166us/step - loss: 0.3486 - accuracy: 0.9102 -
val_loss: 0.1394 - val_accuracy: 0.9635
Epoch 8/20
60000/60000 [==============================] - 10s 167us/step - loss: 0.3130 - accuracy: 0.9202 -
val_loss: 0.1312 - val_accuracy: 0.9672
Epoch 9/20
60000/60000 [==============================] - 10s 170us/step - loss: 0.2941 - accuracy: 0.9265 -
val_loss: 0.1244 - val_accuracy: 0.9688
Epoch 10/20
60000/60000 [==============================] - 10s 171us/step - loss: 0.2699 - accuracy: 0.9320 -
val_loss: 0.1168 - val_accuracy: 0.9719
Epoch 11/20
60000/60000 [==============================] - 10s 167us/step - loss: 0.2502 - accuracy: 0.9392 -
val_loss: 0.1138 - val_accuracy: 0.9739
Epoch 12/20
60000/60000 [==============================] - 10s 167us/step - loss: 0.2459 - accuracy: 0.9414 -
val_loss: 0.1119 - val_accuracy: 0.9746
Epoch 13/20
60000/60000 [==============================] - 10s 166us/step - loss: 0.2271 - accuracy: 0.9462 -
val_loss: 0.1104 - val_accuracy: 0.9750
Epoch 14/20
60000/60000 [==============================] - 10s 166us/step - loss: 0.2120 - accuracy: 0.9502 -
val_loss: 0.1035 - val_accuracy: 0.9737
Epoch 15/20
60000/60000 [==============================] - 10s 166us/step - loss: 0.2085 - accuracy: 0.9510 -
val_loss: 0.1047 - val_accuracy: 0.9763
Epoch 16/20
60000/60000 [==============================] - 10s 166us/step - loss: 0.1989 - accuracy: 0.9536 -
val_loss: 0.1012 - val_accuracy: 0.9760
Epoch 17/20
60000/60000 [==============================] - 10s 168us/step - loss: 0.1892 - accuracy: 0.9559 -
val_loss: 0.1004 - val_accuracy: 0.9776
Epoch 18/20
60000/60000 [==============================] - 10s 167us/step - loss: 0.1859 - accuracy: 0.9575 -
val_loss: 0.0933 - val_accuracy: 0.9787
Epoch 19/20
60000/60000 [==============================] - 10s 166us/step - loss: 0.1772 - accuracy: 0.9597 -
val_loss: 0.0994 - val_accuracy: 0.9781
Epoch 20/20
60000/60000 [==============================] - 10s 166us/step - loss: 0.1726 - accuracy: 0.9591 -
val_loss: 0.1029 - val_accuracy: 0.9760
```

val_loss: 0.1029 - val_accuracy: 0.9760

In [132]:

```
score = model_drop.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))

# print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, va
lidation_data=(X_test, Y_test))

# we will get val_loss and val_acc only when you pass the paramter validation_data
# val_loss : validation loss
# val_acc : validation accuracy

# loss : training loss
# acc : train accuracy
# for each key in histrory.histrory we will have a list of length equal to number of epochs

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

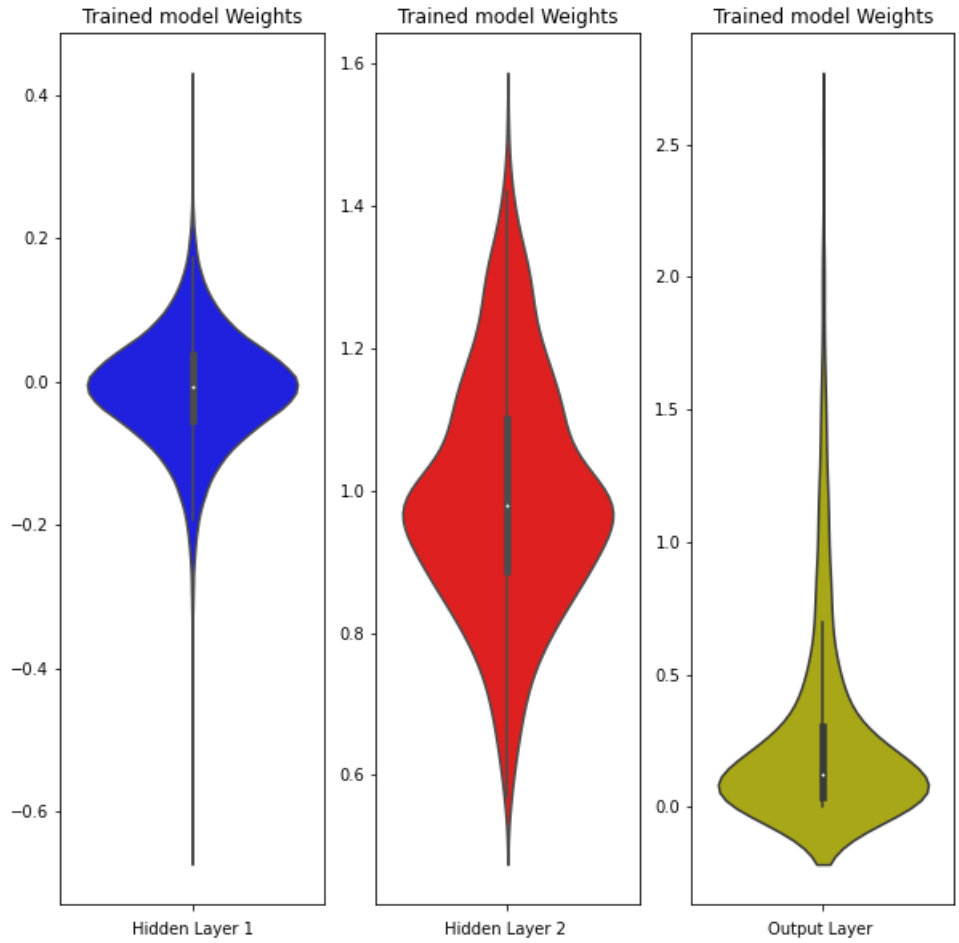
```
Test score: 0.10285850774878635
Test accuracy: 0.9760000109672546
```



In [133]:

```
w_after = model_drop.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(figsize=(10,10))
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 ')

#We have 5 hidden layers but we are only plotting distribution of only two layers
plt.subplot(1, 3, 3)
plt.title("Trained model Weights")
```

```
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output Layer ')
plt.show()
```



Comparing models using prettytable library

Without using Batch Normalization and Dropout

In [140]:

```
from prettytable import PrettyTable
x=PrettyTable()

x.field_names=["#Layers","Architecture","Activation","Optimizer","Intializer","Test
Score/Accuracy"] #column headers

x.add_row(["2", "256-64","Relu","Adam","RandomNormal","0.0899/0.980"])
x.add_row(["3", "512-256-128","Relu","Adam","RandomNormal","0.102/0.980"])
x.add_row(["5", "512-256-128-64-32","Relu","Adam","RandomNormal","0.076/0.982"])
print(x)
```

```
+---------+-------------------+------------+-----------+--------------+----------------------+
| #Layers |    Architecture   | Activation | Optimizer |  Intializer  | Test Score/Accuracy |
+---------+-------------------+------------+-----------+--------------+----------------------+
|    2    |       256-64      |    Relu    |    Adam   | RandomNormal |     0.0899/0.980     |
|    3    |    512-256-128    |    Relu    |    Adam   | RandomNormal |     0.102/0.980      |
|    5    | 512-256-128-64-32 |    Relu    |    Adam   | RandomNormal |     0.076/0.982      |
+---------+-------------------+------------+-----------+--------------+----------------------+
```

Using Batch Normalization

In [139]:

```
from prettytable import PrettyTable
x=PrettyTable()

x.field_names=["#Layers","Architecture","Activation","Optimizer","Intializer","Test
Score/Accuracy"] #column headers

x.add_row(["2", "256-64","Relu","Adam","RandomNormal","0.0934/0.976"])
x.add_row(["3", "512-256-128","Relu","Adam","RandomNormal","0.076/0.981"])
x.add_row(["5", "512-256-128-64-32","Relu","Adam","RandomNormal","0.074/0.981"])
print(x)
```

```
+---------+-------------------+------------+-----------+--------------+---------------------+
| #Layers |    Architecture   | Activation | Optimizer |  Intializer  | Test Score/Accuracy |
+---------+-------------------+------------+-----------+--------------+---------------------+
|    2    |       256-64      |    Relu    |    Adam   | RandomNormal |     0.0934/0.976    |
|    3    |    512-256-128    |    Relu    |    Adam   | RandomNormal |     0.076/0.981     |
|    5    | 512-256-128-64-32 |    Relu    |    Adam   | RandomNormal |     0.074/0.981     |
+---------+-------------------+------------+-----------+--------------+---------------------+
```

With using Batch Normalization and Dropout

In [138]:

```
from prettytable import PrettyTable
x=PrettyTable()

x.field_names=["#Layers","Architecture","Activation","Optimizer","Intializer","Test
Score/Accuracy"] #column headers

x.add_row(["2", "256-64","Relu","Adam","RandomNormal","0.0712/0.979"])
x.add_row(["3", "512-256-128","Relu","Adam","RandomNormal","0.065/0.981"])
x.add_row(["5", "512-256-128-64-32","Relu","Adam","RandomNormal","0.102/0.976"])
print(x)
```

```
+---------+-------------------+------------+-----------+--------------+---------------------+
| #Layers |    Architecture   | Activation | Optimizer |  Intializer  | Test Score/Accuracy |
+---------+-------------------+------------+-----------+--------------+---------------------+
|    2    |       256-64      |    Relu    |    Adam   | RandomNormal |     0.0712/0.979    |
|    3    |    512-256-128    |    Relu    |    Adam   | RandomNormal |     0.065/0.981     |
|    5    | 512-256-128-64-32 |    Relu    |    Adam   | RandomNormal |     0.102/0.976     |
+---------+-------------------+------------+-----------+--------------+---------------------+
```

In [ ]:

```
```