In [1]:

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

```
C:\Users\Santosh\Anaconda3\lib\site-packages\h5py\__init__.py:72: UserWarning: h5py is running
against HDF5 1.10.2 when it was built against 1.10.3, this may cause problems
  '{0}.{1}.{2}'.format(*version.hdf5_built_version_tuple)
Using TensorFlow backend.
```

In [2]:

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

In [3]:

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

In [4]:

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

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

In [5]:

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

X_train = X_train.reshape(X_train.shape[0], X_train.shape[1]*X_train.shape[2])
X_test = X_test.reshape(X_test.shape[0], X_test.shape[1]*X_test.shape[2])
```

In [6]:

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

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

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

In [7]:

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

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

In [8]:

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

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

In [9]:

```python
# 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.          0.04313725
 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.          0.1372549   0.94509804
 0.88235294  0.62745098  0.42352941  0.00392157  0.          0.
 0.          0.          0.          0.          0.          0.
 0.          0.          0.          0.          0.          0.
 0.          0.          0.          0.          0.          0.
 0.          0.          0.          0.31764706  0.94117647  0.99215686
 0.99215686  0.46666667  0.09803922  0.          0.          0.
 0.          0.          0.          0.          0.          0.
 0.          0.          0.          0.          0.          0.
 0.          0.          0.          0.          0.          0.
 0.          0.          0.17647059  0.72941176  0.99215686  0.99215686
 0.58823529  0.10588235  0.          0.          0.          0.
 0.          0.          0.          0.          0.          0.
 0.          0.          0.          0.          0.          0.
 0.          0.          0.          0.          0.          0.
 0.          0.0627451   0.36470588  0.98823529  0.99215686  0.73333333
 0.          0.          0.          0.          0.          0.
 0.          0.          0.          0.          0.          0.
 0.          0.          0.          0.          0.          0.
 0.          0.          0.          0.          0.          0.
 0.          0.97647059  0.99215686  0.97647059  0.25098039  0.
 0.          0.          0.          0.          0.          0.
 0.          0.          0.          0.          0.          0.
 0.          0.          0.          0.          0.          0.
 0.          0.          0.18039216  0.50980392  0.71764706  0.99215686
 0.99215686  0.81176471  0.00784314  0.          0.          0.
```

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

In [10]:

```
# 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) #one hot incoding
Y_test = np_utils.to_categorical(y_test, 10)#one hot incoding

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

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

## Softmax classifier

In [11]:

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

# The Sequential model is a linear stack of layers.
# 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
from keras.layers import Dense, Activation
```

In [12]:

```
# some model parameters

output_dim = 10
input_dim = X_train.shape[1]

batch_size = 128
nb_epoch = 20
```

In [13]:

```
# start building a model
model = Sequential()#output of one model goe to input to second model

# The model needs to know what input shape it should expect.
# For this reason, the first layer in a Sequential model
# (and only the first, because following layers can do automatic shape inference)
# needs to receive information about its input shape.
# you can use input_shape and input_dim to pass the shape of input

# output_dim represent the number of nodes need in that layer
# here we have 10 nodes

model.add(Dense(output_dim, input_dim=input_dim, activation='softmax'))
```

```
WARNING:tensorflow:From C:\Users\Santosh\Anaconda3\lib\site-
```

```
packages\tensorflow\python\ops\resource_variable_ops.py:435: colocate_with (from
tensorflow.python.framework.ops) is deprecated and will be removed in a future version.
Instructions for updating:
Colocations handled automatically by placer.
```

In [14]:

```
# Before training a model, you need to configure the learning process, which is done via the compi
le method

# It receives three arguments:
# An optimizer. This could be the string identifier of an existing optimizer ,
https://keras.io/optimizers/
# A loss function. This is the objective that the model will try to minimize.,
https://keras.io/losses/
# A list of metrics. For any classification problem you will want to set this to metrics=['accurac
y'].  https://keras.io/metrics/


# Note: when using the categorical_crossentropy loss, your targets should be in categorical format

# (e.g. if you have 10 classes, the target for each sample should be a 10-dimensional vector that
is all-zeros except
# for a 1 at the index corresponding to the class of the sample).

# that is why we converted out labels into vectors

model.compile(optimizer='sgd', loss='categorical_crossentropy', metrics=['accuracy'])

# Keras models are trained on Numpy arrays of input data and labels.
# For training a model, you will typically use the  fit function

# fit(self, x=None, y=None, batch_size=None, epochs=1, verbose=1, callbacks=None,
validation_split=0.0,
# validation_data=None, shuffle=True, class_weight=None, sample_weight=None, initial_epoch=0, step
s_per_epoch=None,
# validation_steps=None)

# fit() function Trains the model for a fixed number of epochs (iterations on a dataset).

# it returns A History object. Its History.history attribute is a record of training loss values a
nd
# metrics values at successive epochs, as well as validation loss values and validation metrics va
lues (if applicable).

# https://github.com/openai/baselines/issues/20

history = model.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, validation
_data=(X_test, Y_test))
```

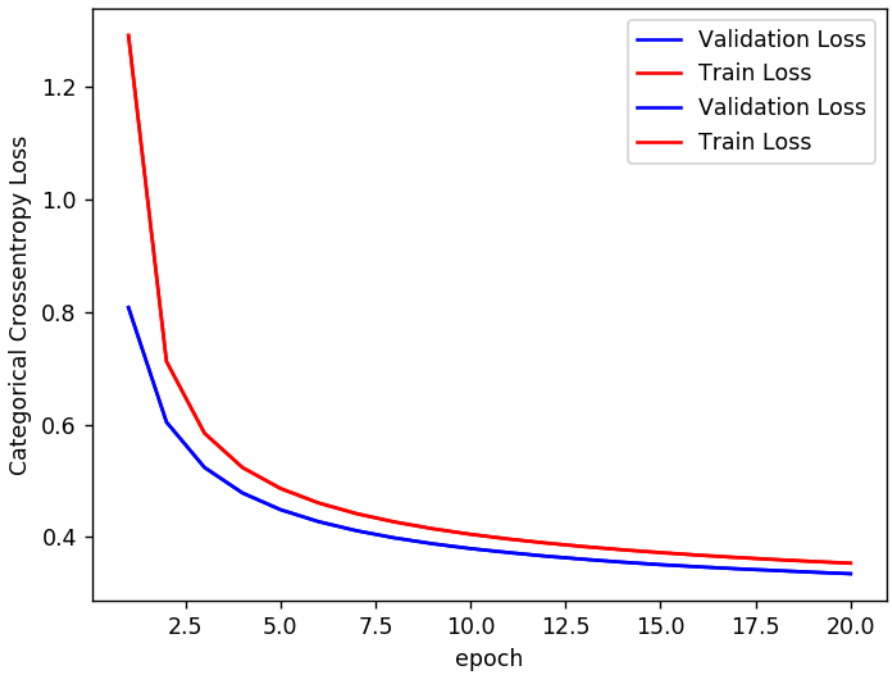
```
WARNING:tensorflow:From C:\Users\Santosh\Anaconda3\lib\site-
packages\tensorflow\python\ops\math_ops.py:3066: to_int32 (from tensorflow.python.ops.math_ops) is
deprecated and will be removed in a future version.
Instructions for updating:
Use tf.cast instead.
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 7s 122us/step - loss: 1.2908 - accuracy: 0.7057 - v
al_loss: 0.8079 - val_accuracy: 0.8374
Epoch 2/20
60000/60000 [==============================] - 6s 98us/step - loss: 0.7120 - accuracy: 0.8432 - va
l_loss: 0.6044 - val_accuracy: 0.8636
Epoch 3/20
60000/60000 [==============================] - 6s 107us/step - loss: 0.5846 - accuracy: 0.8598 - v
al_loss: 0.5238 - val_accuracy: 0.8743
Epoch 4/20
60000/60000 [==============================] - 6s 104us/step - loss: 0.5236 - accuracy: 0.8687 - v
al_loss: 0.4785 - val_accuracy: 0.8811
Epoch 5/20
60000/60000 [==============================] - 6s 97us/step - loss: 0.4865 - accuracy: 0.8753 - va
l_loss: 0.4488 - val_accuracy: 0.8860
Epoch 6/20
60000/60000 [==============================] - 6s 93us/step - loss: 0.4608 - accuracy: 0.8804 - va
l_loss: 0.4276 - val_accuracy: 0.8900
Epoch 7/20
```

```
60000/60000 [==============================] - 6s 93us/step - loss: 0.4418 - accuracy: 0.8841 - va
l_loss: 0.4115 - val_accuracy: 0.8920
Epoch 8/20
60000/60000 [==============================] - 6s 95us/step - loss: 0.4270 - accuracy: 0.8868 - va
l_loss: 0.3987 - val_accuracy: 0.8946
Epoch 9/20
60000/60000 [==============================] - 6s 98us/step - loss: 0.4151 - accuracy: 0.8893 - va
l_loss: 0.3884 - val_accuracy: 0.8971
Epoch 10/20
60000/60000 [==============================] - 6s 103us/step - loss: 0.4051 - accuracy: 0.8914 - v
al_loss: 0.3797 - val_accuracy: 0.8999
Epoch 11/20
60000/60000 [==============================] - 6s 107us/step - loss: 0.3967 - accuracy: 0.8929 - v
al_loss: 0.3727 - val_accuracy: 0.9017
Epoch 12/20
60000/60000 [==============================] - 6s 103us/step - loss: 0.3895 - accuracy: 0.8944 - v
al_loss: 0.3662 - val_accuracy: 0.9036
Epoch 13/20
60000/60000 [==============================] - 6s 97us/step - loss: 0.3831 - accuracy: 0.8957 - va
l_loss: 0.3607 - val_accuracy: 0.9040
Epoch 14/20
60000/60000 [==============================] - 6s 96us/step - loss: 0.3776 - accuracy: 0.8968 - va
l_loss: 0.3556 - val_accuracy: 0.9050
Epoch 15/20
60000/60000 [==============================] - 6s 98us/step - loss: 0.3726 - accuracy: 0.8977 - va
l_loss: 0.3512 - val_accuracy: 0.9055
Epoch 16/20
60000/60000 [==============================] - 6s 93us/step - loss: 0.3681 - accuracy: 0.8989 - va
l_loss: 0.3474 - val_accuracy: 0.9068
Epoch 17/20
60000/60000 [==============================] - 6s 96us/step - loss: 0.3640 - accuracy: 0.8997 - va
l_loss: 0.3439 - val_accuracy: 0.9076
Epoch 18/20
60000/60000 [==============================] - 6s 97us/step - loss: 0.3603 - accuracy: 0.9004 - va
l_loss: 0.3409 - val_accuracy: 0.9088
Epoch 19/20
60000/60000 [==============================] - 6s 94us/step - loss: 0.3569 - accuracy: 0.9012 - va
l_loss: 0.3378 - val_accuracy: 0.9094
Epoch 20/20
60000/60000 [==============================] - 6s 103us/step - loss: 0.3538 - accuracy: 0.9024 - v
al_loss: 0.3351 - val_accuracy: 0.9092
```

In [15]:

```python
score = model.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: 0.3350615925729275
Test accuracy: 0.9092000126838684
```




# MLP + ReLu activation + Adam Optimizer + 2-Layer( experiment)

In [16]:

```
from keras.models import Sequential
from keras.layers import Dense, Activation
from keras.initializers import he_normal

# some model parameters
output_dim = 10
input_dim = X_train.shape[1]
batch_size = 128
nb_epoch = 20


# start building a model
model_1 = Sequential()

# first hidden layer
model_1.add(Dense(364, activation='relu', input_shape=(input_dim,), kernel_initializer=he_normal(se
ed=None)))
# second hidden layer
model_1.add(Dense(52, activation='relu', kernel_initializer=he_normal(seed=None)))

# output layer
model_1.add(Dense(output_dim, activation='softmax'))

model_1.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_2 (Dense)              (None, 364)               285740
_________________________________________________________________
dense_3 (Dense)              (None, 52)                18980
_________________________________________________________________
dense_4 (Dense)              (None, 10)                530
=================================================================
Total params: 305,250
Trainable params: 305,250
Non-trainable params: 0
_________________________________________________________________
```

In [17]:

```
model_1.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history1 = model_1.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, validat
ion_data=(X_test, Y_test))
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 26s 431us/step - loss: 0.2756 - accuracy: 0.9209 -
val_loss: 0.1319 - val_accuracy: 0.9601
Epoch 2/20
60000/60000 [==============================] - 21s 352us/step - loss: 0.1037 - accuracy: 0.9700 -
val_loss: 0.0869 - val_accuracy: 0.9747
Epoch 3/20
60000/60000 [==============================] - 16s 269us/step - loss: 0.0686 - accuracy: 0.9795 -
val_loss: 0.0716 - val_accuracy: 0.9787
Epoch 4/20
60000/60000 [==============================] - 15s 251us/step - loss: 0.0476 - accuracy: 0.9858 -
val_loss: 0.0716 - val_accuracy: 0.9776
Epoch 5/20
60000/60000 [==============================] - 15s 257us/step - loss: 0.0357 - accuracy: 0.9889 -
val_loss: 0.0649 - val_accuracy: 0.9797
Epoch 6/20
60000/60000 [==============================] - 15s 247us/step - loss: 0.0283 - accuracy: 0.9913 -
val_loss: 0.0697 - val_accuracy: 0.9797
Epoch 7/20
60000/60000 [==============================] - 16s 265us/step - loss: 0.0198 - accuracy: 0.9939 -
val_loss: 0.0679 - val_accuracy: 0.9808
Epoch 8/20
60000/60000 [==============================] - 15s 251us/step - loss: 0.0155 - accuracy: 0.9952 -
val_loss: 0.0704 - val_accuracy: 0.9808
Epoch 9/20
60000/60000 [==============================] - 15s 252us/step - loss: 0.0131 - accuracy: 0.9959 -
val_loss: 0.0751 - val_accuracy: 0.9802
Epoch 10/20
60000/60000 [==============================] - 15s 250us/step - loss: 0.0130 - accuracy: 0.9958 -
val_loss: 0.0813 - val_accuracy: 0.9780
Epoch 11/20
60000/60000 [==============================] - 16s 267us/step - loss: 0.0123 - accuracy: 0.9962 -
val_loss: 0.0818 - val_accuracy: 0.9791
Epoch 12/20
60000/60000 [==============================] - 16s 266us/step - loss: 0.0067 - accuracy: 0.9980 -
val_loss: 0.0863 - val_accuracy: 0.9783
Epoch 13/20
60000/60000 [==============================] - 16s 271us/step - loss: 0.0065 - accuracy: 0.9978 -
val_loss: 0.0970 - val_accuracy: 0.9774
Epoch 14/20
60000/60000 [==============================] - 16s 274us/step - loss: 0.0110 - accuracy: 0.9962 -
val_loss: 0.0842 - val_accuracy: 0.9810
Epoch 15/20
60000/60000 [==============================] - 16s 269us/step - loss: 0.0078 - accuracy: 0.9974 -
val_loss: 0.0840 - val_accuracy: 0.9812
Epoch 16/20
60000/60000 [==============================] - 15s 255us/step - loss: 0.0068 - accuracy: 0.9978 -
val_loss: 0.0903 - val_accuracy: 0.9809
Epoch 17/20
60000/60000 [==============================] - 16s 271us/step - loss: 0.0051 - accuracy: 0.9984 -
val_loss: 0.0914 - val_accuracy: 0.9802
Epoch 18/20
60000/60000 [==============================] - 16s 260us/step - loss: 0.0075 - accuracy: 0.9973 -
val_loss: 0.1008 - val_accuracy: 0.9791
Epoch 19/20
60000/60000 [==============================] - 17s 284us/step - loss: 0.0092 - accuracy: 0.9968 -
val_loss: 0.0926 - val_accuracy: 0.9802
Epoch 20/20
60000/60000 [==============================] - 16s 260us/step - loss: 0.0056 - accuracy: 0.9982 -
val_loss: 0.0960 - val_accuracy: 0.9801
```

In [18]:

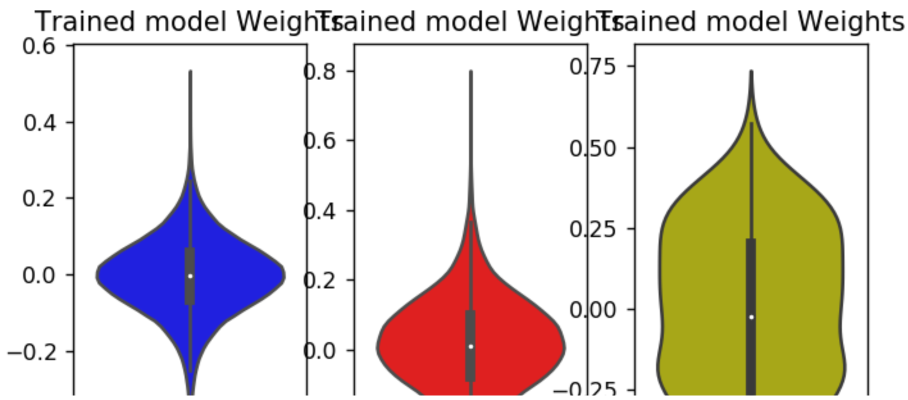
```
score = model_1.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
```

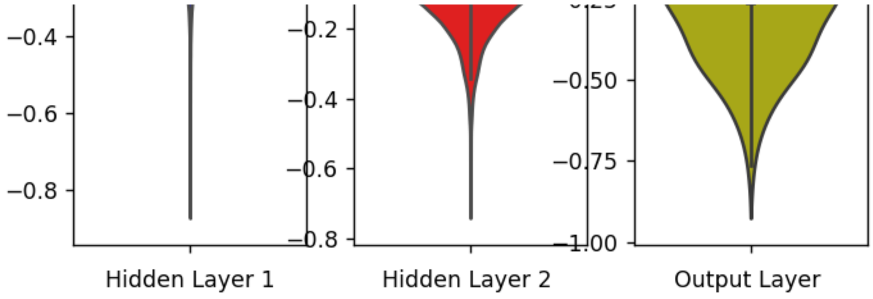
```
print('Test accuracy:', score[1])

#fig,ax = plt.subplots(1,1)
#ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')
model_1_test_score = score[0]
model_1_test_acc = score[1]
model_1_train = history1.history['accuracy']

# 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: 0.096045138551638
Test accuracy: 0.9800999760627747
```

In [19]:

```
w_after = model_1.get_weights()

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


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

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

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






# MLP + Sigmoid activation + ADAM

In [20]:

```
model_sigmoid = Sequential()
model_sigmoid.add(Dense(512, activation='sigmoid', input_shape=(input_dim,)))
model_sigmoid.add(Dense(128, activation='sigmoid'))
model_sigmoid.add(Dense(output_dim, activation='softmax'))

model_sigmoid.summary()

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

history = model_sigmoid.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, va
lidation_data=(X_test, Y_test))
```

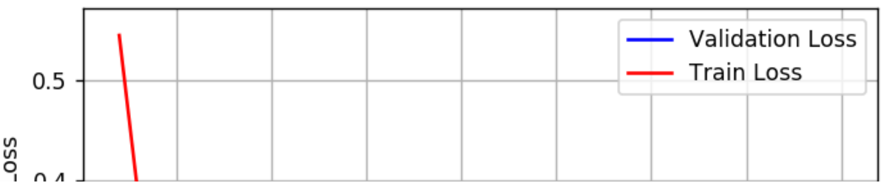
```
Model: "sequential_3"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_5 (Dense)              (None, 512)               401920    
_________________________________________________________________
dense_6 (Dense)              (None, 128)               65664     
_________________________________________________________________
dense_7 (Dense)              (None, 10)                1290      
=================================================================
Total params: 468,874
Trainable params: 468,874
Non-trainable params: 0
_________________________________________________________________
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 21s 345us/step - loss: 0.5455 - accuracy: 0.8561 -
val_loss: 0.2505 - val_accuracy: 0.9285
Epoch 2/20
60000/60000 [==============================] - 20s 327us/step - loss: 0.2222 - accuracy: 0.9345 -
val_loss: 0.1821 - val_accuracy: 0.9473
Epoch 3/20
60000/60000 [==============================] - 20s 330us/step - loss: 0.1638 - accuracy: 0.9510 -
val_loss: 0.1462 - val_accuracy: 0.9581
Epoch 4/20
60000/60000 [==============================] - 19s 317us/step - loss: 0.1264 - accuracy: 0.9631 -
val_loss: 0.1243 - val_accuracy: 0.9636
Epoch 5/20
60000/60000 [==============================] - 20s 338us/step - loss: 0.0991 - accuracy: 0.9709 -
val_loss: 0.1033 - val_accuracy: 0.9680
Epoch 6/20
60000/60000 [==============================] - 19s 322us/step - loss: 0.0791 - accuracy: 0.9768 -
val_loss: 0.0953 - val_accuracy: 0.9708
Epoch 7/20
60000/60000 [==============================] - 20s 329us/step - loss: 0.0640 - accuracy: 0.9809 -
val_loss: 0.0839 - val_accuracy: 0.9731
Epoch 8/20
60000/60000 [==============================] - 31s 514us/step - loss: 0.0516 - accuracy: 0.9843 -
val_loss: 0.0728 - val_accuracy: 0.9777- loss: 0.0519 - accuracy - ETA: 14s - loss:  - ETA: 12s -
loss: 0.0518 - accu - ETA: 12s - l - ETA: 0s - loss: 0.0517
Epoch 9/20
60000/60000 [==============================] - 23s 387us/step - loss: 0.0423 - accuracy: 0.9876 -
val_loss: 0.0772 - val_accuracy: 0.9750
Epoch 10/20
60000/60000 [==============================] - 23s 380us/step - loss: 0.0337 - accuracy: 0.9906 -
```

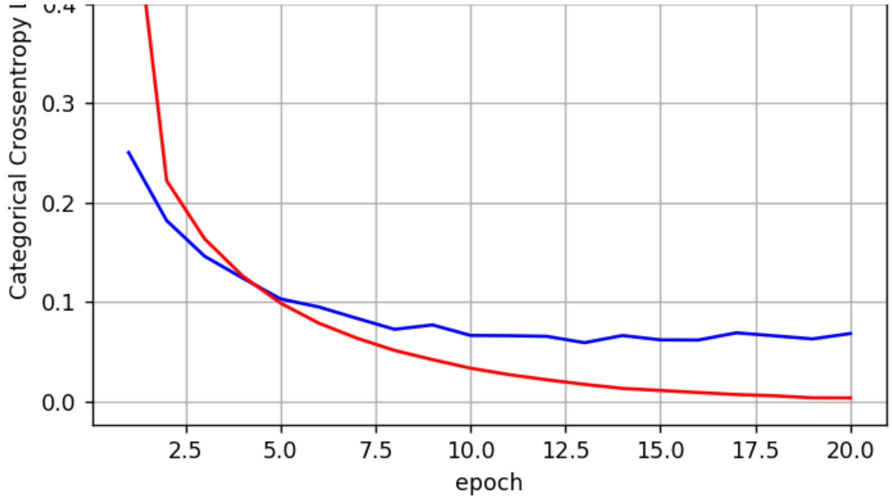
```
val_loss: 0.0666 - val_accuracy: 0.9798
Epoch 11/20
60000/60000 [==============================] - 20s 329us/step - loss: 0.0273 - accuracy: 0.9924 -
val_loss: 0.0664 - val_accuracy: 0.9795
Epoch 12/20
60000/60000 [==============================] - 18s 304us/step - loss: 0.0221 - accuracy: 0.9939 -
val_loss: 0.0657 - val_accuracy: 0.9811
Epoch 13/20
60000/60000 [==============================] - 18s 306us/step - loss: 0.0175 - accuracy: 0.9955 -
val_loss: 0.0593 - val_accuracy: 0.9824
Epoch 14/20
60000/60000 [==============================] - 19s 310us/step - loss: 0.0134 - accuracy: 0.9970 -
val_loss: 0.0665 - val_accuracy: 0.9807
Epoch 15/20
60000/60000 [==============================] - 18s 305us/step - loss: 0.0113 - accuracy: 0.9973 -
val_loss: 0.0622 - val_accuracy: 0.9815
Epoch 16/20
60000/60000 [==============================] - 19s 317us/step - loss: 0.0092 - accuracy: 0.9980 -
val_loss: 0.0620 - val_accuracy: 0.9816
Epoch 17/20
60000/60000 [==============================] - 19s 309us/step - loss: 0.0072 - accuracy: 0.9984 -
val_loss: 0.0693 - val_accuracy: 0.9814
Epoch 18/20
60000/60000 [==============================] - 18s 304us/step - loss: 0.0060 - accuracy: 0.9987 -
val_loss: 0.0662 - val_accuracy: 0.9812
Epoch 19/20
60000/60000 [==============================] - 18s 303us/step - loss: 0.0039 - accuracy: 0.9993 -
val_loss: 0.0631 - val_accuracy: 0.9825
Epoch 20/20
60000/60000 [==============================] - 18s 307us/step - loss: 0.0038 - accuracy: 0.9992 -
val_loss: 0.0685 - val_accuracy: 0.9825
```

In [21]:

```python
score = model_sigmoid.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)
```

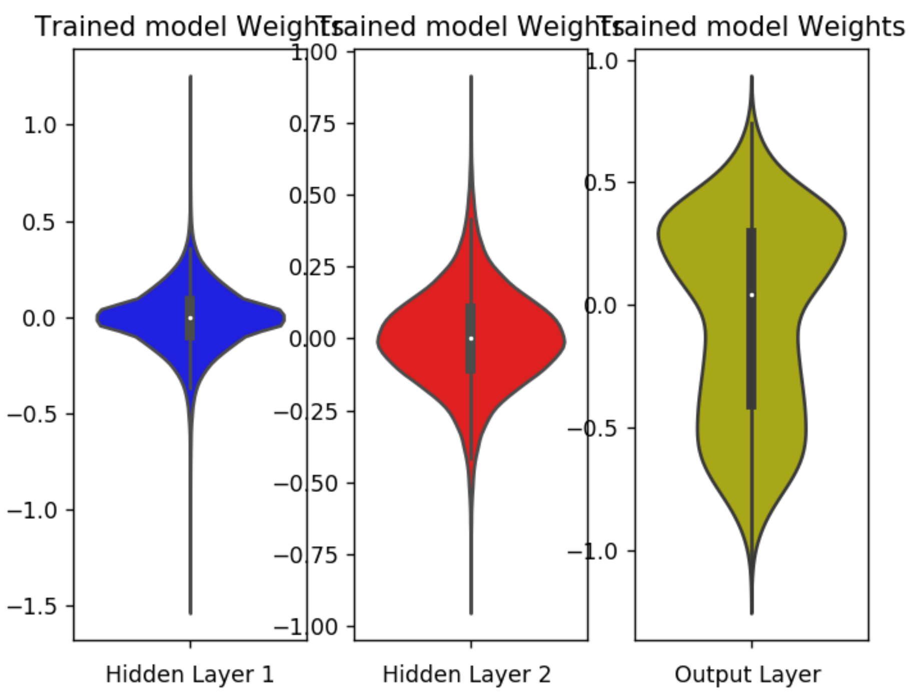
```
Test score: 0.06853543838825717
Test accuracy: 0.9825000166893005
```






In [22]:

```
w_after = model_sigmoid.get_weights()

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


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

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

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



## MLP + ReLU +SGD

In [23]:

```
# Multilayer perceptron

# https://arxiv.org/pdf/1707.09725.pdf#page=95
# for relu layers
# If we sample weights from a normal distribution N(0,σ) we satisfy this condition with
σ=√(2/(ni).
# h1 =>  σ=√(2/(fan_in) = 0.062  => N(0,σ) = N(0,0.062)
# h2 =>  σ=√(2/(fan_in) = 0.125  => N(0,σ) = N(0,0.125)
# out =>  σ=√(2/(fan_in+1) = 0.120  => N(0,σ) = N(0,0.120)

model_relu = Sequential()
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(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()
```

```
Model: "sequential_4"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_8 (Dense)              (None, 512)               401920
_________________________________________________________________
dense_9 (Dense)              (None, 128)               65664
_________________________________________________________________
dense_10 (Dense)             (None, 10)                1290
=================================================================
Total params: 468,874
Trainable params: 468,874
Non-trainable params: 0
_________________________________________________________________
```

In [24]:

```
model_relu.compile(optimizer='sgd', 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))
```

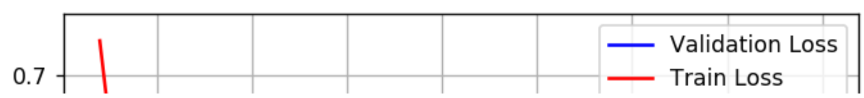
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 15s 243us/step - loss: 0.7408 - accuracy: 0.7910 -
val_loss: 0.3847 - val_accuracy: 0.8978
Epoch 2/20
60000/60000 [==============================] - 14s 228us/step - loss: 0.3568 - accuracy: 0.8990 -
val_loss: 0.3001 - val_accuracy: 0.9165
Epoch 3/20
60000/60000 [==============================] - 14s 239us/step - loss: 0.2936 - accuracy: 0.9163 -
val_loss: 0.2635 - val_accuracy: 0.9263
Epoch 4/20
60000/60000 [==============================] - 14s 227us/step - loss: 0.2579 - accuracy: 0.9269 -
val_loss: 0.2385 - val_accuracy: 0.9330
Epoch 5/20
60000/60000 [==============================] - 14s 241us/step - loss: 0.2333 - accuracy: 0.9340 -
val_loss: 0.2203 - val_accuracy: 0.9382
Epoch 6/20
60000/60000 [==============================] - 14s 241us/step - loss: 0.2143 - accuracy: 0.9393 -
val_loss: 0.2050 - val_accuracy: 0.9416
Epoch 7/20
60000/60000 [==============================] - 13s 225us/step - loss: 0.1989 - accuracy: 0.9442 -
val_loss: 0.1951 - val_accuracy: 0.9433
Epoch 8/20
60000/60000 [==============================] - 14s 226us/step - loss: 0.1859 - accuracy: 0.9479 -
val_loss: 0.1849 - val_accuracy: 0.9458
Epoch 9/20
```

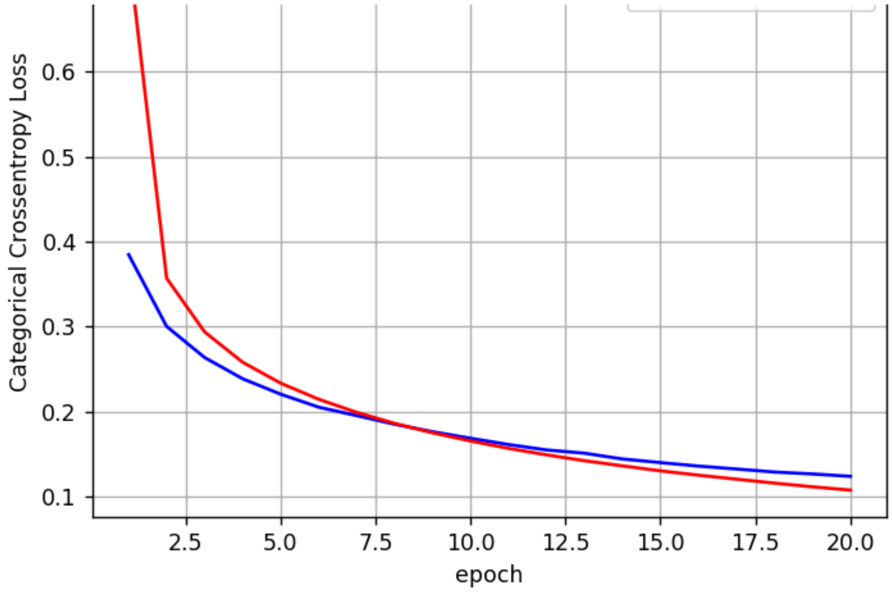
```
60000/60000 [==============================] - 14s 225us/step - loss: 0.1748 - accuracy: 0.9510 -
val_loss: 0.1761 - val_accuracy: 0.9484
Epoch 10/20
60000/60000 [==============================] - 14s 227us/step - loss: 0.1652 - accuracy: 0.9539 -
val_loss: 0.1683 - val_accuracy: 0.9501
Epoch 11/20
60000/60000 [==============================] - 14s 226us/step - loss: 0.1564 - accuracy: 0.9567 -
val_loss: 0.1610 - val_accuracy: 0.9527
Epoch 12/20
60000/60000 [==============================] - 14s 231us/step - loss: 0.1489 - accuracy: 0.9589 -
val_loss: 0.1546 - val_accuracy: 0.9538
Epoch 13/20
60000/60000 [==============================] - 14s 233us/step - loss: 0.1419 - accuracy: 0.9606 -
val_loss: 0.1508 - val_accuracy: 0.9561
Epoch 14/20
60000/60000 [==============================] - 17s 286us/step - loss: 0.1358 - accuracy: 0.9624 -
val_loss: 0.1439 - val_accuracy: 0.9583
Epoch 15/20
60000/60000 [==============================] - 16s 273us/step - loss: 0.1300 - accuracy: 0.9644 -
val_loss: 0.1397 - val_accuracy: 0.9581
Epoch 16/20
60000/60000 [==============================] - 15s 245us/step - loss: 0.1249 - accuracy: 0.9658 -
val_loss: 0.1356 - val_accuracy: 0.9601
Epoch 17/20
60000/60000 [==============================] - 14s 239us/step - loss: 0.1202 - accuracy: 0.9671 -
val_loss: 0.1321 - val_accuracy: 0.9608
Epoch 18/20
60000/60000 [==============================] - 14s 232us/step - loss: 0.1155 - accuracy: 0.9682 -
val_loss: 0.1286 - val_accuracy: 0.9619
Epoch 19/20
60000/60000 [==============================] - 14s 226us/step - loss: 0.1112 - accuracy: 0.9701 -
val_loss: 0.1263 - val_accuracy: 0.9612
Epoch 20/20
60000/60000 [==============================] - 14s 227us/step - loss: 0.1073 - accuracy: 0.9708 -
val_loss: 0.1235 - val_accuracy: 0.9632
```

In [25]:

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

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

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

# 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)
```

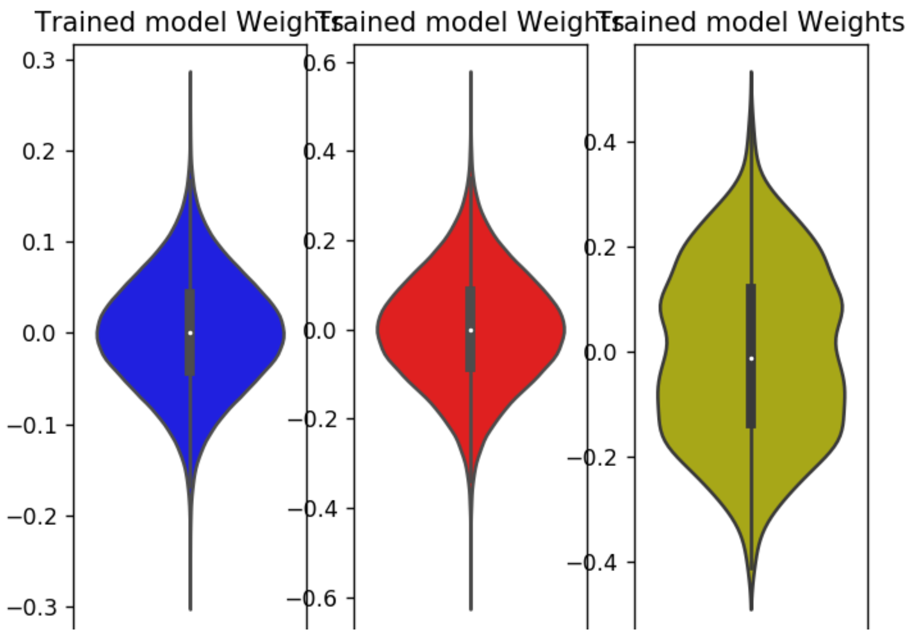
```
Test score: 0.12351691169328988
Test accuracy: 0.9631999731063843
```

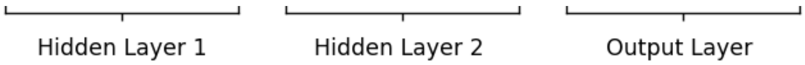





In [26]:

```
w_after = model_relu.get_weights()

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


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

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

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






## MLP + ReLU + ADAM

In [27]:

```
model_relu = Sequential()
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(128, 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))
```

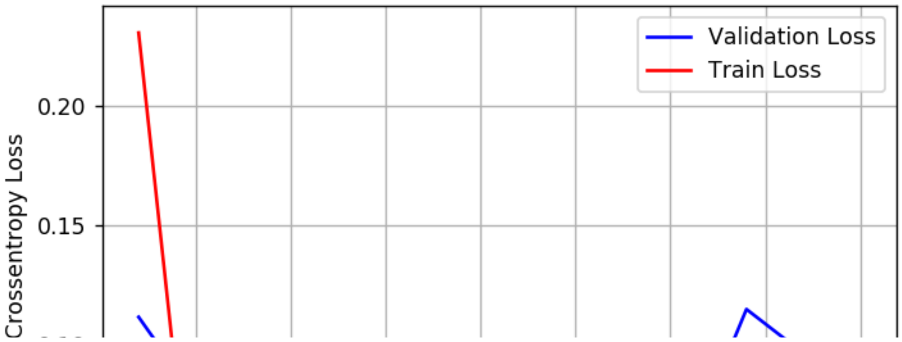
```
Model: "sequential_5"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_11 (Dense)             (None, 512)               401920    
_________________________________________________________________
dense_12 (Dense)             (None, 128)               65664     
_________________________________________________________________
dense_13 (Dense)             (None, 10)                1290      
=================================================================
Total params: 468,874
Trainable params: 468,874
Non-trainable params: 0
_________________________________________________________________
None
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 20s 329us/step - loss: 0.2307 - accuracy: 0.9318 -
val_loss: 0.1117 - val_accuracy: 0.9657
Epoch 2/20
60000/60000 [==============================] - 18s 305us/step - loss: 0.0838 - accuracy: 0.9743 -
val_loss: 0.0892 - val_accuracy: 0.9723
Epoch 3/20
60000/60000 [==============================] - 19s 310us/step - loss: 0.0531 - accuracy: 0.9833 -
val_loss: 0.0723 - val_accuracy: 0.9794
Epoch 4/20
60000/60000 [==============================] - 18s 306us/step - loss: 0.0366 - accuracy: 0.9887 -
val_loss: 0.0748 - val_accuracy: 0.9765
Epoch 5/20
60000/60000 [==============================] - 18s 304us/step - loss: 0.0267 - accuracy: 0.9919 -
val_loss: 0.0720 - val_accuracy: 0.9791
Epoch 6/20
60000/60000 [==============================] - 18s 306us/step - loss: 0.0211 - accuracy: 0.9930 -
val_loss: 0.0820 - val_accuracy: 0.9770
Epoch 7/20
60000/60000 [==============================] - 19s 309us/step - loss: 0.0173 - accuracy: 0.9941 -
val_loss: 0.0654 - val_accuracy: 0.9825
Epoch 8/20
60000/60000 [==============================] - 18s 306us/step - loss: 0.0136 - accuracy: 0.9956 -
val_loss: 0.0693 - val_accuracy: 0.9814
Epoch 9/20
60000/60000 [==============================] - 19s 317us/step - loss: 0.0119 - accuracy: 0.9959 -
val_loss: 0.0652 - val_accuracy: 0.9817
Epoch 10/20
60000/60000 [==============================] - 18s 305us/step - loss: 0.0113 - accuracy: 0.9960 -
val_loss: 0.0735 - val_accuracy: 0.9818
Epoch 11/20
60000/60000 [==============================] - 24s 405us/step - loss: 0.0131 - accuracy: 0.9959 -
val_loss: 0.0829 - val_accuracy: 0.9802
Epoch 12/20
60000/60000 [==============================] - 19s 320us/step - loss: 0.0092 - accuracy: 0.9969 -
val_loss: 0.0718 - val_accuracy: 0.9819
```

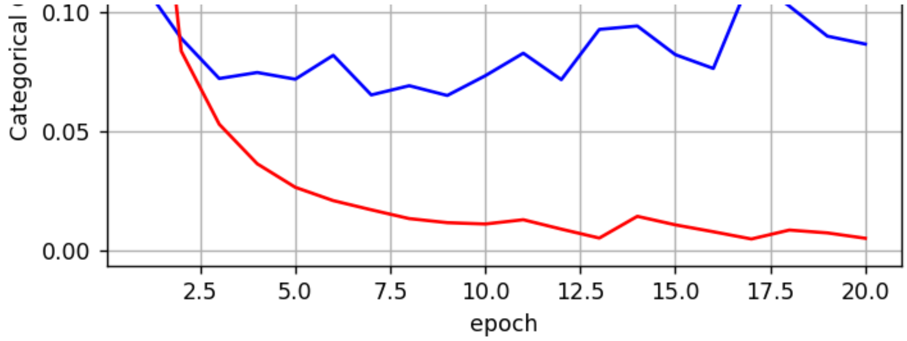
```
val_loss: 0.0718 - val_accuracy: 0.9819
Epoch 13/20
60000/60000 [==============================] - 19s 311us/step - loss: 0.0054 - accuracy: 0.9981 -
val_loss: 0.0929 - val_accuracy: 0.9811
Epoch 14/20
60000/60000 [==============================] - 21s 347us/step - loss: 0.0145 - accuracy: 0.9950 -
val_loss: 0.0943 - val_accuracy: 0.9793
Epoch 15/20
60000/60000 [==============================] - 31s 511us/step - loss: 0.0110 - accuracy: 0.9965 -
val_loss: 0.0823 - val_accuracy: 0.9824
Epoch 16/20
60000/60000 [==============================] - 30s 497us/step - loss: 0.0081 - accuracy: 0.9972 -
val_loss: 0.0765 - val_accuracy: 0.9824
Epoch 17/20
60000/60000 [==============================] - 28s 468us/step - loss: 0.0050 - accuracy: 0.9982 -
val_loss: 0.1150 - val_accuracy: 0.9761
Epoch 18/20
60000/60000 [==============================] - 19s 314us/step - loss: 0.0088 - accuracy: 0.9974 -
val_loss: 0.1027 - val_accuracy: 0.9776
Epoch 19/20
60000/60000 [==============================] - 18s 304us/step - loss: 0.0076 - accuracy: 0.9977 -
val_loss: 0.0901 - val_accuracy: 0.9818
Epoch 20/20
60000/60000 [==============================] - 18s 307us/step - loss: 0.0053 - accuracy: 0.9984 -
val_loss: 0.0867 - val_accuracy: 0.9815
```

In [28]:

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

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

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

# 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)
```

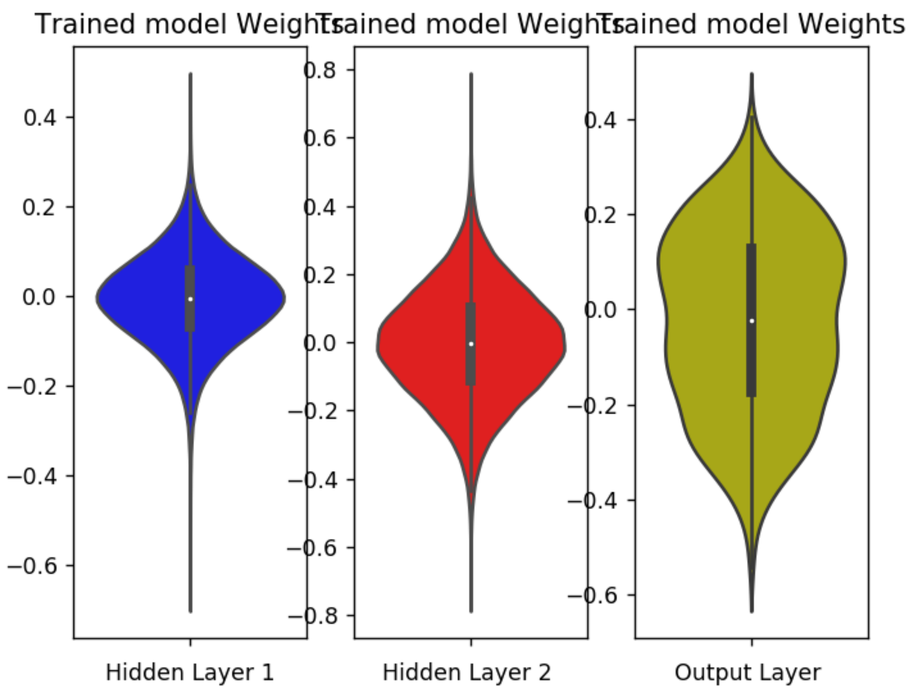
```
Test score: 0.08674870625808599
Test accuracy: 0.9815000295639038
```






In [29]:

```
w_after = model_relu.get_weights()

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


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

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

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




### MLP + Batch-Norm on hidden Layers + AdamOptimizer

In [30]:

```
# Multilayer perceptron

# https://intoli.com/blog/neural-network-initialization/
# If we sample weights from a normal distribution N(0,σ) we satisfy this condition with
σ=√(2/(ni+ni+1).
# h1 =>  σ=√(2/(ni+ni+1) = 0.039  => N(0,σ) = N(0,0.039)
# h2 =>  σ=√(2/(ni+ni+1) = 0.055  => N(0,σ) = N(0,0.055)
# h1 =>  σ=√(2/(ni+ni+1) = 0.120  => N(0,σ) = N(0,0.120)

from keras.layers.normalization import BatchNormalization

model_batch = Sequential()

model_batch.add(Dense(512, activation='sigmoid', input_shape=(input_dim,), kernel_initializer=Rando
mNormal(mean=0.0, stddev=0.039, seed=None)))
model_batch.add(BatchNormalization())

model_batch.add(Dense(128, activation='sigmoid', 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_6"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_14 (Dense)             (None, 512)               401920
_________________________________________________________________
batch_normalization_1 (Batch (None, 512)               2048
_________________________________________________________________
dense_15 (Dense)             (None, 128)               65664
_________________________________________________________________
batch_normalization_2 (Batch (None, 128)               512
_________________________________________________________________
dense_16 (Dense)             (None, 10)                1290
=================================================================
Total params: 471,434
Trainable params: 470,154
Non-trainable params: 1,280
_________________________________________________________________
```

In [31]:

```
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))
```

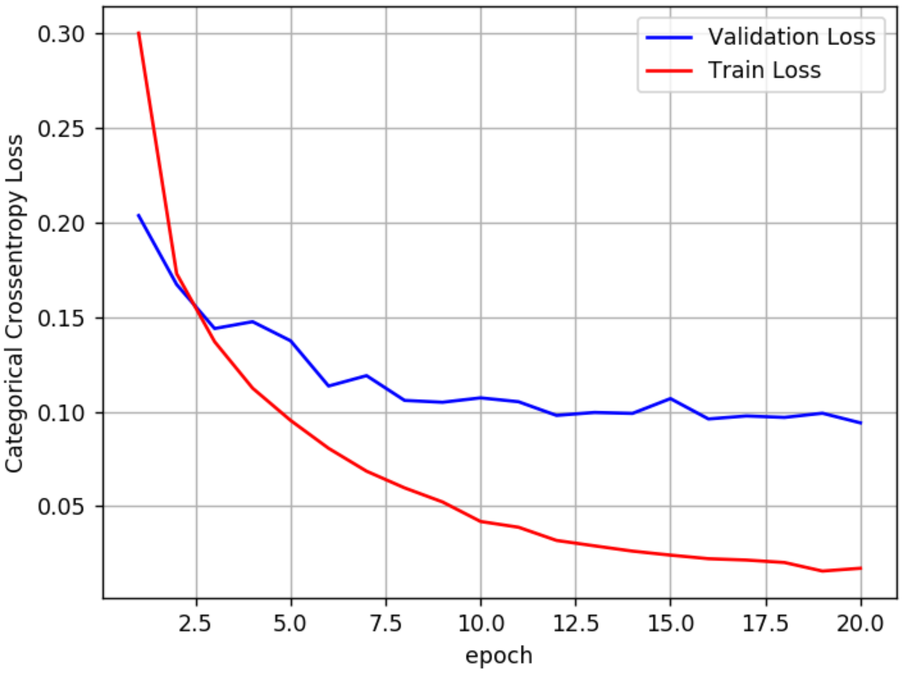
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 31s 519us/step - loss: 0.2999 - accuracy: 0.9111 -
val_loss: 0.2035 - val_accuracy: 0.9412
Epoch 2/20
60000/60000 [==============================] - 22s 370us/step - loss: 0.1729 - accuracy: 0.9496 -
val_loss: 0.1672 - val_accuracy: 0.9512
Epoch 3/20
60000/60000 [==============================] - 23s 381us/step - loss: 0.1369 - accuracy: 0.9591 -
val_loss: 0.1439 - val_accuracy: 0.9567
Epoch 4/20
60000/60000 [==============================] - 23s 379us/step - loss: 0.1124 - accuracy: 0.9660 -
val_loss: 0.1475 - val_accuracy: 0.9559
Epoch 5/20
60000/60000 [==============================] - 22s 372us/step - loss: 0.0954 - accuracy: 0.9707 -
val_loss: 0.1374 - val_accuracy: 0.9566
Epoch 6/20
60000/60000 [==============================] - 21s 354us/step - loss: 0.0807 - accuracy: 0.9749 -
val_loss: 0.1135 - val_accuracy: 0.9646
Epoch 7/20
60000/60000 [==============================] - 21s 353us/step - loss: 0.0686 - accuracy: 0.9786 -
```

```
val_loss: 0.1190 - val_accuracy: 0.96320.0687 - accuracy
Epoch 8/20
60000/60000 [==============================] - 32s 534us/step - loss: 0.0598 - accuracy: 0.9816 -
val_loss: 0.1059 - val_accuracy: 0.9667
Epoch 9/20
60000/60000 [==============================] - 27s 448us/step - loss: 0.0523 - accuracy: 0.9835 -
val_loss: 0.1050 - val_accuracy: 0.9697: 0.0524 - accuracy: 0.
Epoch 10/20
60000/60000 [==============================] - 23s 388us/step - loss: 0.0420 - accuracy: 0.9862 -
val_loss: 0.1073 - val_accuracy: 0.9677
Epoch 11/20
60000/60000 [==============================] - 21s 354us/step - loss: 0.0390 - accuracy: 0.9877 -
val_loss: 0.1052 - val_accuracy: 0.9699
Epoch 12/20
60000/60000 [==============================] - 21s 354us/step - loss: 0.0320 - accuracy: 0.9897 -
val_loss: 0.0980 - val_accuracy: 0.9706
Epoch 13/20
60000/60000 [==============================] - 21s 358us/step - loss: 0.0292 - accuracy: 0.9905 -
val_loss: 0.0996 - val_accuracy: 0.9702
Epoch 14/20
60000/60000 [==============================] - 25s 410us/step - loss: 0.0264 - accuracy: 0.9915 -
val_loss: 0.0991 - val_accuracy: 0.9717
Epoch 15/20
60000/60000 [==============================] - 24s 395us/step - loss: 0.0243 - accuracy: 0.9922 -
val_loss: 0.1069 - val_accuracy: 0.9701
Epoch 16/20
60000/60000 [==============================] - 26s 428us/step - loss: 0.0224 - accuracy: 0.9925 -
val_loss: 0.0962 - val_accuracy: 0.9718
Epoch 17/20
60000/60000 [==============================] - 26s 437us/step - loss: 0.0217 - accuracy: 0.9928 -
val_loss: 0.0977 - val_accuracy: 0.9740
Epoch 18/20
60000/60000 [==============================] - 22s 370us/step - loss: 0.0204 - accuracy: 0.9934 -
val_loss: 0.0970 - val_accuracy: 0.9729
Epoch 19/20
60000/60000 [==============================] - 22s 369us/step - loss: 0.0158 - accuracy: 0.9950 -
val_loss: 0.0992 - val_accuracy: 0.9749
Epoch 20/20
60000/60000 [==============================] - 24s 397us/step - loss: 0.0173 - accuracy: 0.9942 -
val_loss: 0.0941 - val_accuracy: 0.9742
```

In [32]:

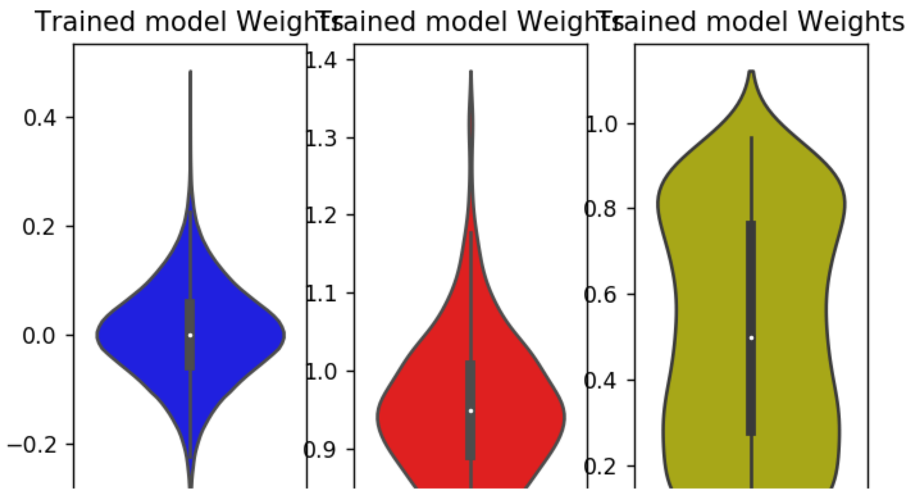
```
score = model_batch.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

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)
```

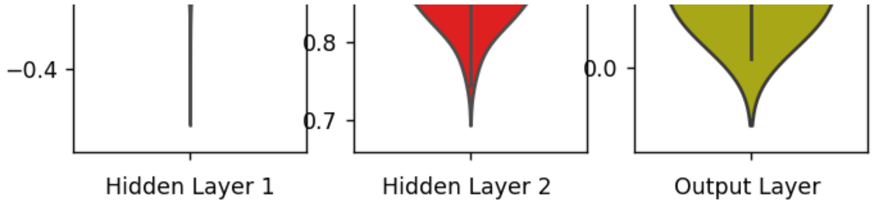
```
Test score: 0.09408825902347454
Test accuracy: 0.9742000102996826
```




In [33]:

```
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()
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()
```






## 5. MLP + Dropout + AdamOptimizer

In [34]:

```
# 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='sigmoid', 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(128, activation='sigmoid', 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_7"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_17 (Dense)             (None, 512)               401920
_________________________________________________________________
batch_normalization_3 (Batch (None, 512)               2048
_________________________________________________________________
dropout_1 (Dropout)          (None, 512)               0
_________________________________________________________________
dense_18 (Dense)             (None, 128)               65664
_________________________________________________________________
batch_normalization_4 (Batch (None, 128)               512
_________________________________________________________________
dropout_2 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_19 (Dense)             (None, 10)                1290
=================================================================
Total params: 471,434
Trainable params: 470,154
Non-trainable params: 1,280
_________________________________________________________________
```

In [35]:

```
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, validation_data=(X_test, Y_test))
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 27s 448us/step - loss: 0.6754 - accuracy: 0.7914 - val_loss: 0.2864 - val_accuracy: 0.9169
Epoch 2/20
60000/60000 [==============================] - 24s 407us/step - loss: 0.4325 - accuracy: 0.8675 - val_loss: 0.2540 - val_accuracy: 0.9259
```

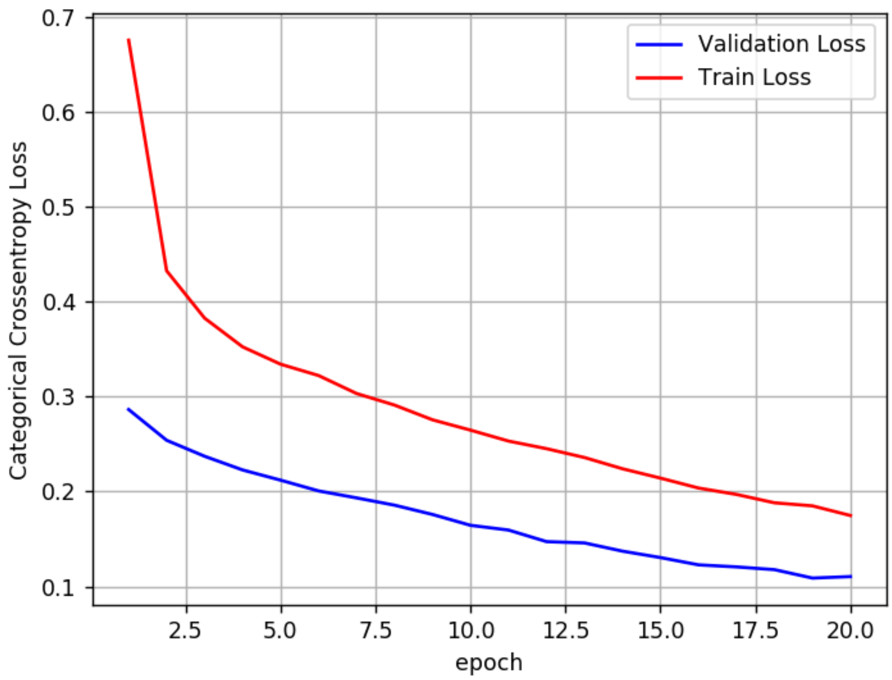
```
Epoch 3/20
60000/60000 [==============================] - 24s 399us/step - loss: 0.3827 - accuracy: 0.8835 -
val_loss: 0.2372 - val_accuracy: 0.9300
Epoch 4/20
60000/60000 [==============================] - 28s 466us/step - loss: 0.3524 - accuracy: 0.8935 -
val_loss: 0.2228 - val_accuracy: 0.9339
Epoch 5/20
60000/60000 [==============================] - 28s 468us/step - loss: 0.3342 - accuracy: 0.8978 -
val_loss: 0.2121 - val_accuracy: 0.9381
Epoch 6/20
60000/60000 [==============================] - 24s 403us/step - loss: 0.3222 - accuracy: 0.9033 -
val_loss: 0.2007 - val_accuracy: 0.9391
Epoch 7/20
60000/60000 [==============================] - 25s 415us/step - loss: 0.3033 - accuracy: 0.9075 -
val_loss: 0.1934 - val_accuracy: 0.9422
Epoch 8/20
60000/60000 [==============================] - 27s 444us/step - loss: 0.2911 - accuracy: 0.9113 -
val_loss: 0.1857 - val_accuracy: 0.9449
Epoch 9/20
60000/60000 [==============================] - 25s 414us/step - loss: 0.2756 - accuracy: 0.9163 -
val_loss: 0.1759 - val_accuracy: 0.9469
Epoch 10/20
60000/60000 [==============================] - 27s 449us/step - loss: 0.2647 - accuracy: 0.9201 -
val_loss: 0.1645 - val_accuracy: 0.9515
Epoch 11/20
60000/60000 [==============================] - 24s 399us/step - loss: 0.2532 - accuracy: 0.9239 -
val_loss: 0.1595 - val_accuracy: 0.9523
Epoch 12/20
60000/60000 [==============================] - 25s 412us/step - loss: 0.2452 - accuracy: 0.9260 -
val_loss: 0.1473 - val_accuracy: 0.9558
Epoch 13/20
60000/60000 [==============================] - 24s 408us/step - loss: 0.2359 - accuracy: 0.9292 -
val_loss: 0.1460 - val_accuracy: 0.9557
Epoch 14/20
60000/60000 [==============================] - 24s 404us/step - loss: 0.2241 - accuracy: 0.9333 -
val_loss: 0.1373 - val_accuracy: 0.9583
Epoch 15/20
60000/60000 [==============================] - 31s 518us/step - loss: 0.2142 - accuracy: 0.9362 -
val_loss: 0.1305 - val_accuracy: 0.9617
Epoch 16/20
60000/60000 [==============================] - 26s 438us/step - loss: 0.2038 - accuracy: 0.9382 -
val_loss: 0.1229 - val_accuracy: 0.9635
Epoch 17/20
60000/60000 [==============================] - 24s 404us/step - loss: 0.1970 - accuracy: 0.9402 -
val_loss: 0.1207 - val_accuracy: 0.9644
Epoch 18/20
60000/60000 [==============================] - 25s 413us/step - loss: 0.1882 - accuracy: 0.9438 -
val_loss: 0.1178 - val_accuracy: 0.9653
Epoch 19/20
60000/60000 [==============================] - 26s 430us/step - loss: 0.1850 - accuracy: 0.9449 -
val_loss: 0.1090 - val_accuracy: 0.9673
Epoch 20/20
60000/60000 [==============================] - 27s 454us/step - loss: 0.1748 - accuracy: 0.9481 -
val_loss: 0.1105 - val_accuracy: 0.9682
```

In [36]:

```
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
```

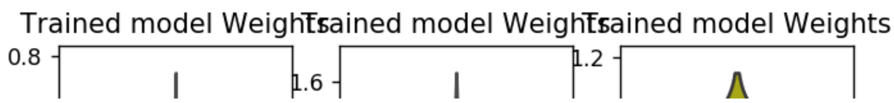
```
# loss : training loss
# acc : train accuracy
# for each key in histrory.histrory we will have a list of length equal to number of epochs

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

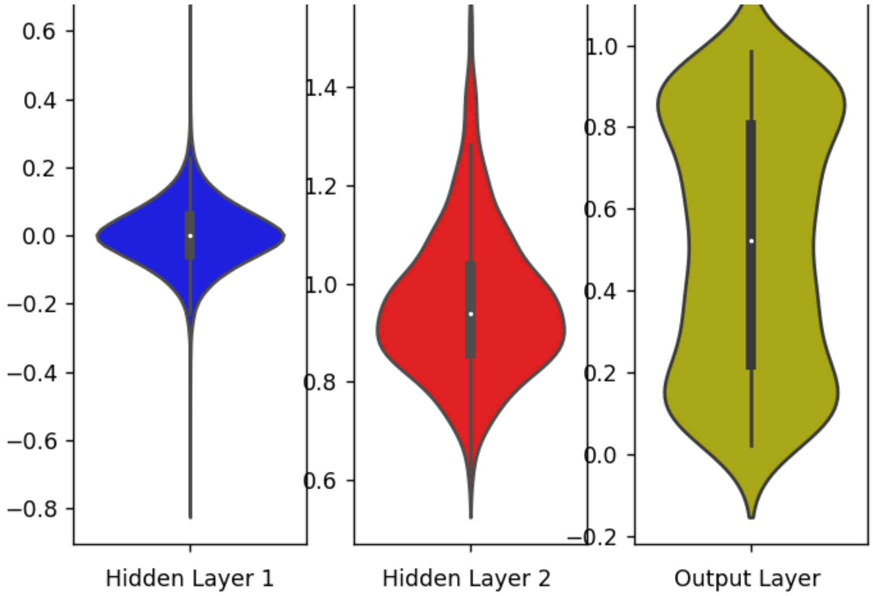
```
Test score: 0.11052532543241977
Test accuracy: 0.9682000279426575
```




In [37]:

```
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()
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()
```






## Hyper-parameter tuning of Keras models using Sklearn

In [38]:

```
from keras.optimizers import Adam,RMSprop,SGD
def best_hyperparameters(activ):

    model = Sequential()
    model.add(Dense(512, activation=activ, input_shape=(input_dim,), kernel_initializer=RandomNorma
l(mean=0.0, stddev=0.062, seed=None)))
    model.add(Dense(128, activation=activ, kernel_initializer=RandomNormal(mean=0.0, stddev=0.125,
seed=None)) )
    model.add(Dense(output_dim, activation='softmax'))


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

    return model
```

In [39]:

```
 #https://machinelearningmastery.com/grid-search-hyperparameters-deep-learning-models-python-keras
/

activ = ['sigmoid','relu']

from keras.wrappers.scikit_learn import KerasClassifier
from sklearn.model_selection import GridSearchCV

model = KerasClassifier(build_fn=best_hyperparameters, epochs=nb_epoch, batch_size=batch_size, verb
ose=0)
param_grid = dict(activ=activ)

# if you are using CPU
# grid = GridSearchCV(estimator=model, param_grid=param_grid, n_jobs=-1)
# if you are using GPU dont use the n_jobs parameter

grid = GridSearchCV(estimator=model, param_grid=param_grid)
grid_result = grid.fit(X_train, Y_train)
```

```
C:\Users\Santosh\Anaconda3\lib\site-packages\sklearn\model_selection\_split.py:2053:
FutureWarning: You should specify a value for 'cv' instead of relying on the default value. The de
fault value will change from 3 to 5 in version 0.22.
  warnings.warn(CV_WARNING, FutureWarning)
```

In [40]:

```
print("Best: %f using %s" % (grid_result.best_score_, grid_result.best_params_))
```

```
means = grid_result.cv_results_['mean_test_score']
stds = grid_result.cv_results_['std_test_score']
params = grid_result.cv_results_['params']
for mean, stdev, param in zip(means, stds, params):
    print("%f (%f) with: %r" % (mean, stdev, param))
```

```
Best: 0.977733 using {'activ': 'relu'}
0.975183 (0.001243) with: {'activ': 'sigmoid'}
0.977733 (0.001759) with: {'activ': 'relu'}
```

# Assignment

### Using Activation= relu, Optimizer= Adam

#### 2 Hidden Layers, 3 Hidden Layers, 5 Hidden Layers.

In [47]:

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

from keras.layers import Dropout
from keras.layers.normalization import BatchNormalization

from keras.models import Sequential
from keras.layers import Dense, Activation
from keras.initializers import he_normal


#paramter
output_dim = 10
input_dim = X_train.shape[1]

batch_size = 128
nb_epoch = 20
```

## MLP + ReLu + Adam + BN+Dropout(0.5)+ 2-Layer

In [48]:

```
# Initialising model
model_1 = Sequential()

# First hidden Layer
model_1.add(Dense(364, activation='relu', input_shape=(input_dim,), kernel_initializer=he_normal(seed=None)))

model_1.add(BatchNormalization())

model_1.add(Dropout(0.5))

# second hidden layer
model_1.add(Dense(52, activation='relu', kernel_initializer=he_normal(seed=None)))

model_1.add(BatchNormalization())

model_1.add(Dropout(0.5))

# output layer
model_1.add(Dense(output_dim, activation='softmax'))


model_1.summary()
```

```
Model: "sequential_16"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_44 (Dense)             (None, 364)               285740
```

```
_________________________________________________________________
batch_normalization_7 (Batch (None, 364)               1456
_________________________________________________________________
dropout_5 (Dropout)          (None, 364)               0
_________________________________________________________________
dense_45 (Dense)             (None, 52)                18980
_________________________________________________________________
batch_normalization_8 (Batch (None, 52)                208
_________________________________________________________________
dropout_6 (Dropout)          (None, 52)                0
_________________________________________________________________
dense_46 (Dense)             (None, 10)                530
=================================================================
Total params: 306,914
Trainable params: 306,082
Non-trainable params: 832
_________________________________________________________________
```

In [49]:

```
model_1.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history_m1 = model_1.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, valid
ation_data=(X_test, Y_test))
```

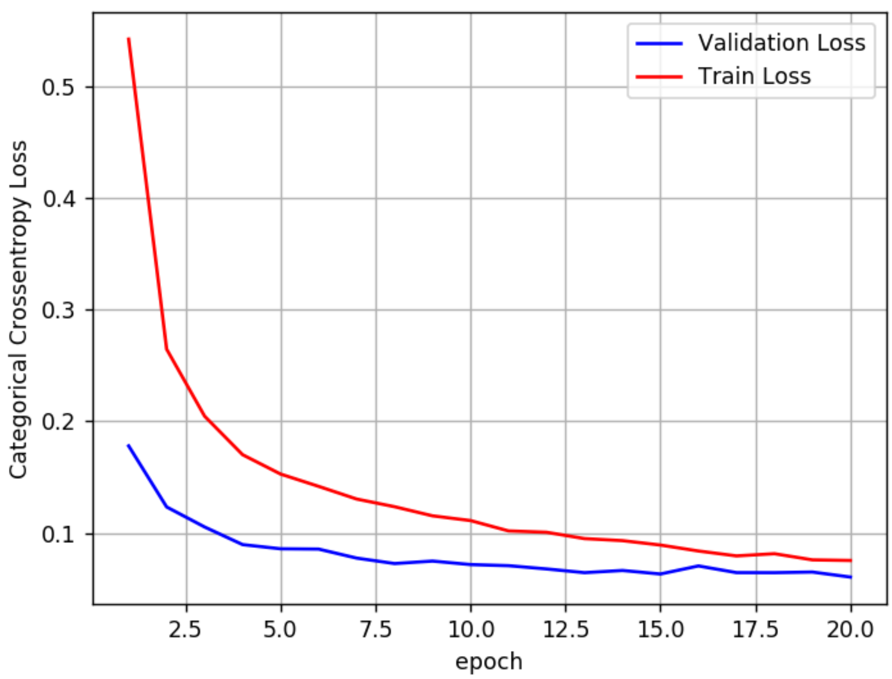
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 43s 722us/step - loss: 0.5421 - accuracy: 0.8371 -
val_loss: 0.1780 - val_accuracy: 0.9477
Epoch 2/20
60000/60000 [==============================] - 36s 595us/step - loss: 0.2645 - accuracy: 0.9241 -
val_loss: 0.1233 - val_accuracy: 0.9611
Epoch 3/20
60000/60000 [==============================] - 33s 550us/step - loss: 0.2045 - accuracy: 0.9413 -
val_loss: 0.1054 - val_accuracy: 0.9679
Epoch 4/20
60000/60000 [==============================] - 32s 536us/step - loss: 0.1701 - accuracy: 0.9503 -
val_loss: 0.0896 - val_accuracy: 0.9714
Epoch 5/20
60000/60000 [==============================] - 34s 570us/step - loss: 0.1528 - accuracy: 0.9555 -
val_loss: 0.0859 - val_accuracy: 0.9718
Epoch 6/20
60000/60000 [==============================] - 35s 584us/step - loss: 0.1418 - accuracy: 0.9587 -
val_loss: 0.0856 - val_accuracy: 0.9741
Epoch 7/20
60000/60000 [==============================] - 34s 574us/step - loss: 0.1304 - accuracy: 0.9624 -
val_loss: 0.0775 - val_accuracy: 0.9763
Epoch 8/20
60000/60000 [==============================] - 34s 571us/step - loss: 0.1235 - accuracy: 0.9645 -
val_loss: 0.0727 - val_accuracy: 0.9784
Epoch 9/20
60000/60000 [==============================] - 35s 583us/step - loss: 0.1154 - accuracy: 0.9664 -
val_loss: 0.0749 - val_accuracy: 0.9784
Epoch 10/20
60000/60000 [==============================] - 35s 575us/step - loss: 0.1111 - accuracy: 0.9672 -
val_loss: 0.0718 - val_accuracy: 0.9777
Epoch 11/20
60000/60000 [==============================] - 34s 568us/step - loss: 0.1019 - accuracy: 0.9698 -
val_loss: 0.0707 - val_accuracy: 0.9783
Epoch 12/20
60000/60000 [==============================] - 34s 568us/step - loss: 0.1007 - accuracy: 0.9702 -
val_loss: 0.0678 - val_accuracy: 0.9794
Epoch 13/20
60000/60000 [==============================] - 34s 564us/step - loss: 0.0950 - accuracy: 0.9718 -
val_loss: 0.0645 - val_accuracy: 0.9810
Epoch 14/20
60000/60000 [==============================] - 34s 567us/step - loss: 0.0932 - accuracy: 0.9731 -
val_loss: 0.0665 - val_accuracy: 0.9808
Epoch 15/20
60000/60000 [==============================] - 34s 568us/step - loss: 0.0892 - accuracy: 0.9730 -
val_loss: 0.0633 - val_accuracy: 0.9818
Epoch 16/20
60000/60000 [==============================] - 34s 565us/step - loss: 0.0839 - accuracy: 0.9751 -
val_loss: 0.0705 - val_accuracy: 0.9800
Epoch 17/20
```

```
60000/60000 [==============================] - 34s 570us/step - loss: 0.0795 - accuracy: 0.9762 -
val_loss: 0.0645 - val_accuracy: 0.9813
Epoch 18/20
60000/60000 [==============================] - 34s 567us/step - loss: 0.0815 - accuracy: 0.9761 -
val_loss: 0.0645 - val_accuracy: 0.9818
Epoch 19/20
60000/60000 [==============================] - 32s 527us/step - loss: 0.0760 - accuracy: 0.9774 -
val_loss: 0.0651 - val_accuracy: 0.9801
Epoch 20/20
60000/60000 [==============================] - 34s 565us/step - loss: 0.0754 - accuracy: 0.9774 -
val_loss: 0.0606 - val_accuracy: 0.9824
```

In [55]:

```
score = model_1.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_m1.history['val_loss']
ty = history_m1.history['loss']
plt_dynamic(x, vy, ty, ax)
```

```
Test score: 0.06056223605640116
Test accuracy: 0.9824000000953674
```

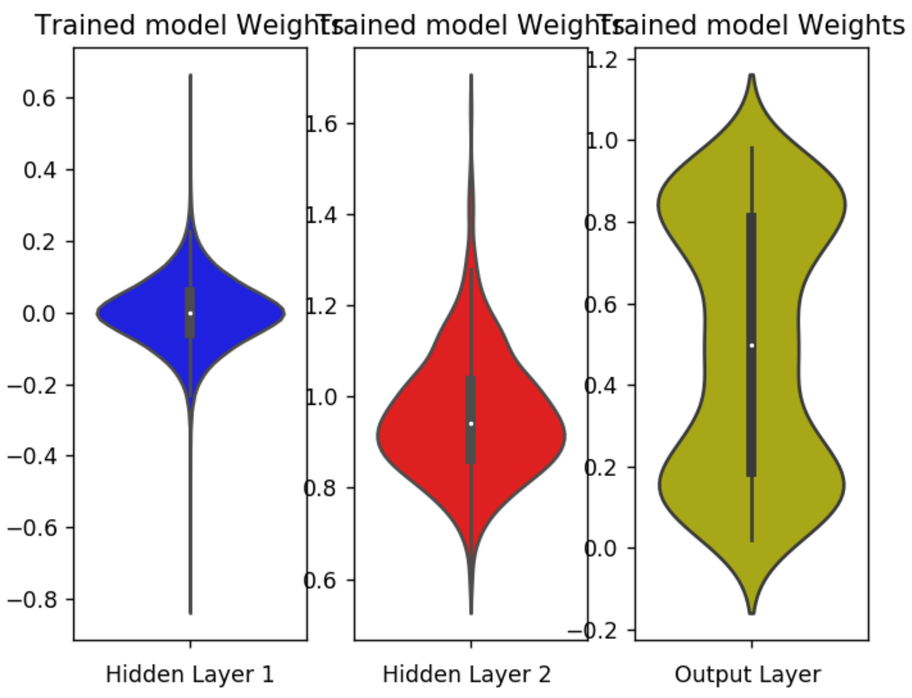


In [ ]:

```

```

In [56]:

```
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()
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()
```




## MLP + Batch-Norm and Dropout(0.2) on 2 hidden Layer

In [41]:

```
from keras.layers.normalization import BatchNormalization
from keras.layers import Dropout

model_12 = Sequential()

model_12.add(Dense(576, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNorma
l(mean=0.0, stddev=0.056, seed=None)))
model_12.add(BatchNormalization())
```

```
model_12.add(Dropout(0.2))

model_12.add(Dense(340, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.068, seed=None)) )
model_12.add(BatchNormalization())
model_12.add(Dropout(0.2))

model_12.add(Dense(output_dim, activation='softmax'))


model_12.summary()
```

```
Model: "sequential_15"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_41 (Dense)             (None, 576)               452160    
_________________________________________________________________
batch_normalization_5 (Batch (None, 576)               2304      
_________________________________________________________________
dropout_3 (Dropout)          (None, 576)               0         
_________________________________________________________________
dense_42 (Dense)             (None, 340)               196180    
_________________________________________________________________
batch_normalization_6 (Batch (None, 340)               1360      
_________________________________________________________________
dropout_4 (Dropout)          (None, 340)               0         
_________________________________________________________________
dense_43 (Dense)             (None, 10)                3410      
=================================================================
Total params: 655,414
Trainable params: 653,582
Non-trainable params: 1,832
_________________________________________________________________
```

In [43]:

```
model_12.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history_12 = model_12.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, validation_data=(X_test, Y_test))
```

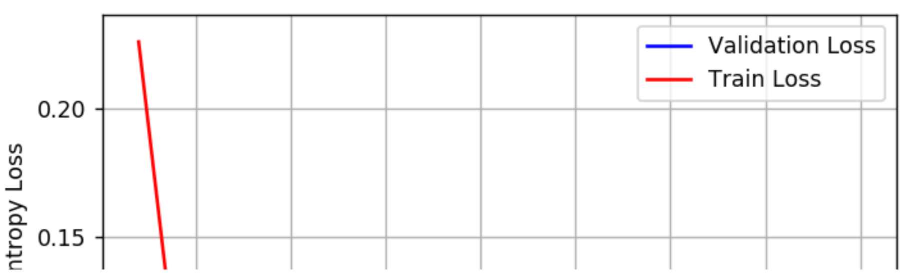
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 45s 753us/step - loss: 0.2261 - accuracy: 0.9310 - val_loss: 0.1076 - val_accuracy: 0.9656
Epoch 2/20
60000/60000 [==============================] - 39s 642us/step - loss: 0.0996 - accuracy: 0.9693 - val_loss: 0.0837 - val_accuracy: 0.9725
Epoch 3/20
60000/60000 [==============================] - 34s 574us/step - loss: 0.0718 - accuracy: 0.9772 - val_loss: 0.0728 - val_accuracy: 0.9781
Epoch 4/20
60000/60000 [==============================] - 33s 553us/step - loss: 0.0575 - accuracy: 0.9816 - val_loss: 0.0691 - val_accuracy: 0.9779
Epoch 5/20
60000/60000 [==============================] - 33s 551us/step - loss: 0.0492 - accuracy: 0.9836 - val_loss: 0.0621 - val_accuracy: 0.9794
Epoch 6/20
60000/60000 [==============================] - 33s 553us/step - loss: 0.0441 - accuracy: 0.9850 - val_loss: 0.0611 - val_accuracy: 0.9801
Epoch 7/20
60000/60000 [==============================] - 33s 549us/step - loss: 0.0357 - accuracy: 0.9880 - val_loss: 0.0642 - val_accuracy: 0.9815
Epoch 8/20
60000/60000 [==============================] - 34s 559us/step - loss: 0.0338 - accuracy: 0.9888 - val_loss: 0.0675 - val_accuracy: 0.9808
Epoch 9/20
60000/60000 [==============================] - 34s 574us/step - loss: 0.0318 - accuracy: 0.9891 - val_loss: 0.0661 - val_accuracy: 0.9823
Epoch 10/20
60000/60000 [==============================] - 33s 553us/step - loss: 0.0271 - accuracy: 0.9914 - val_loss: 0.0723 - val_accuracy: 0.9804
Epoch 11/20
60000/60000 [==============================] - 34s 564us/step - loss: 0.0256 - accuracy: 0.9910 -
```

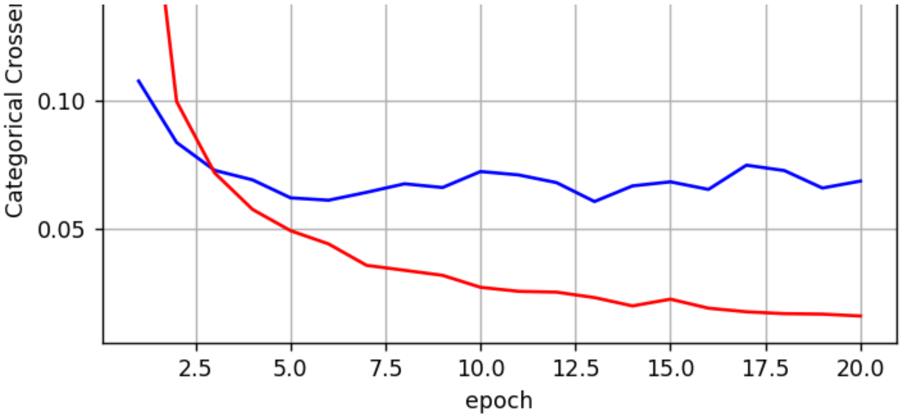
```
val_loss: 0.0710 - val_accuracy: 0.9804
Epoch 12/20
60000/60000 [==============================] - 33s 549us/step - loss: 0.0252 - accuracy: 0.9913 -
val_loss: 0.0680 - val_accuracy: 0.9802
Epoch 13/20
60000/60000 [==============================] - 34s 569us/step - loss: 0.0231 - accuracy: 0.9922 -
val_loss: 0.0606 - val_accuracy: 0.9823
Epoch 14/20
60000/60000 [==============================] - 33s 554us/step - loss: 0.0199 - accuracy: 0.9930 -
val_loss: 0.0667 - val_accuracy: 0.9827
Epoch 15/20
60000/60000 [==============================] - 33s 545us/step - loss: 0.0225 - accuracy: 0.9927 -
val_loss: 0.0683 - val_accuracy: 0.9820
Epoch 16/20
60000/60000 [==============================] - 33s 555us/step - loss: 0.0190 - accuracy: 0.9937 -
val_loss: 0.0654 - val_accuracy: 0.9826
Epoch 17/20
60000/60000 [==============================] - 33s 554us/step - loss: 0.0176 - accuracy: 0.9940 -
val_loss: 0.0748 - val_accuracy: 0.9819
Epoch 18/20
60000/60000 [==============================] - 11s 187us/step - loss: 0.0168 - accuracy: 0.9943 -
val_loss: 0.0727 - val_accuracy: 0.9819
Epoch 19/20
60000/60000 [==============================] - 11s 182us/step - loss: 0.0167 - accuracy: 0.9946 -
val_loss: 0.0659 - val_accuracy: 0.9825
Epoch 20/20
60000/60000 [==============================] - 11s 182us/step - loss: 0.0159 - accuracy: 0.9945 -
val_loss: 0.0686 - val_accuracy: 0.9833
```

In [44]:

```python
score = model_12.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_12.history['val_loss']
ty = history_12.history['loss']
plt_dynamic(x, vy, ty, ax)
```

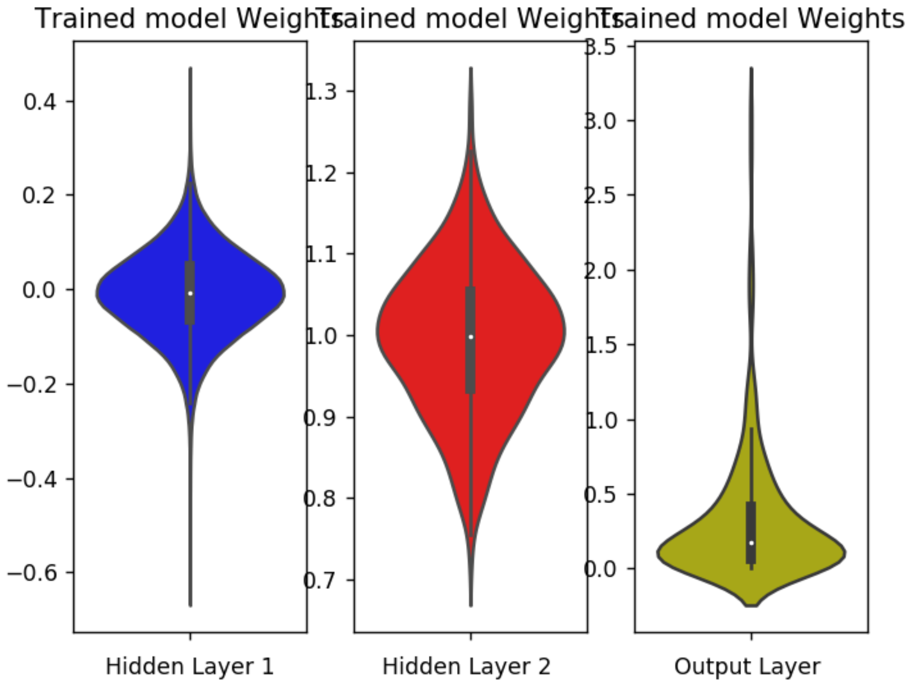
```
Test score: 0.06859428682197286
Test accuracy: 0.983299970626831
```






In [45]:

```
w_after = model_12.get_weights()

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


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

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

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



## MLP + ReLu + Adam+ BN+Dropout(0.5)+ 3-Layer

In [46]:

```
# Initialising model
model_2 = Sequential()

# first hidden layer
model_2.add(Dense(550, activation='relu', input_shape=(input_dim,), kernel_initializer=he_normal(se
ed=None)))
model_2.add(BatchNormalization())
model_2.add(Dropout(0.5))

# second hidden layer
model_2.add(Dense(235, activation='relu', kernel_initializer=he_normal(seed=None)))
model_2.add(BatchNormalization())
model_2.add(Dropout(0.5))

#third hidden layer
model_2.add(Dense(75, activation='relu', kernel_initializer=he_normal(seed=None)))
model_2.add(BatchNormalization())
model_2.add(Dropout(0.5))

model_2.add(Dense(output_dim, activation='softmax'))


model_2.summary()
```

```
Model: "sequential_16"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_44 (Dense)             (None, 550)               431750    
_________________________________________________________________
batch_normalization_7 (Batch (None, 550)               2200      
_________________________________________________________________
dropout_5 (Dropout)          (None, 550)               0         
_________________________________________________________________
dense_45 (Dense)             (None, 235)               129485    
_________________________________________________________________
batch_normalization_8 (Batch (None, 235)               940       
_________________________________________________________________
dropout_6 (Dropout)          (None, 235)               0         
_________________________________________________________________
dense_46 (Dense)             (None, 75)                17700     
_________________________________________________________________
batch_normalization_9 (Batch (None, 75)                300       
_________________________________________________________________
dropout_7 (Dropout)          (None, 75)                0         
_________________________________________________________________
dense_47 (Dense)             (None, 10)                760       
=================================================================
Total params: 583,135
Trainable params: 581,415
Non-trainable params: 1,720
_________________________________________________________________
```

In [47]:

```
model_2.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history_m2= model_2.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, valida
tion_data=(X_test, Y_test))
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 42s 702us/step - loss: 0.5963 - accuracy: 0.8192 -
val_loss: 0.1711 - val_accuracy: 0.9468
Epoch 2/20
60000/60000 [==============================] - 39s 645us/step - loss: 0.2564 - accuracy: 0.9264 -
val_loss: 0.1255 - val_accuracy: 0.9623
Epoch 3/20
60000/60000 [==============================] - 39s 647us/step - loss: 0.2035 - accuracy: 0.9427 -
val_loss: 0.1057 - val_accuracy: 0.9686
```

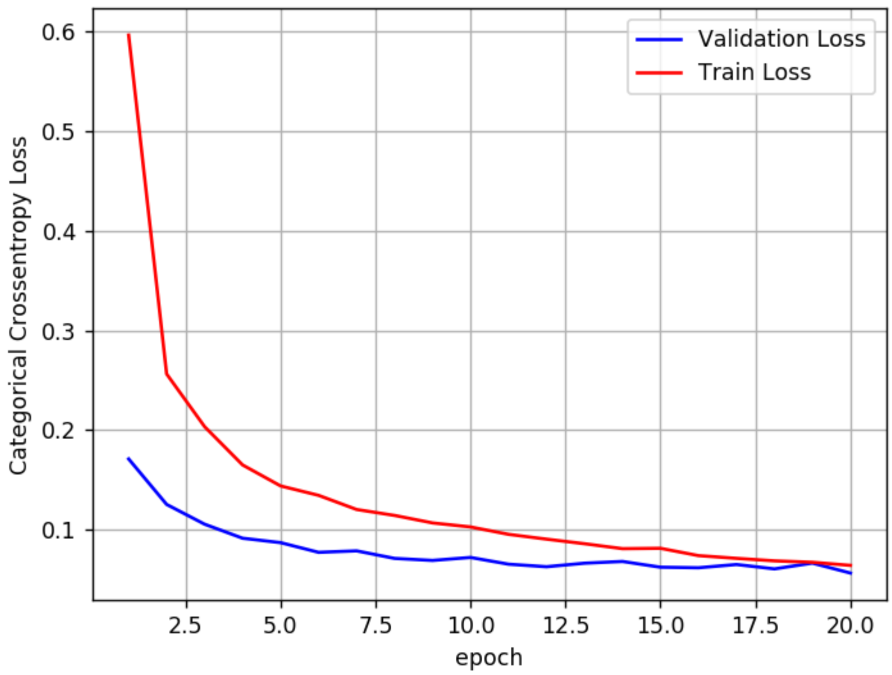
```
Epoch 4/20
60000/60000 [==============================] - 39s 656us/step - loss: 0.1651 - accuracy: 0.9528 -
val_loss: 0.0916 - val_accuracy: 0.9716
Epoch 5/20
60000/60000 [==============================] - 41s 678us/step - loss: 0.1441 - accuracy: 0.9576 -
val_loss: 0.0872 - val_accuracy: 0.9756
Epoch 6/20
60000/60000 [==============================] - 40s 659us/step - loss: 0.1346 - accuracy: 0.9614 -
val_loss: 0.0775 - val_accuracy: 0.9764
Epoch 7/20
60000/60000 [==============================] - 39s 645us/step - loss: 0.1204 - accuracy: 0.9653 -
val_loss: 0.0789 - val_accuracy: 0.9765
Epoch 8/20
60000/60000 [==============================] - 37s 610us/step - loss: 0.1145 - accuracy: 0.9682 -
val_loss: 0.0714 - val_accuracy: 0.9795
Epoch 9/20
60000/60000 [==============================] - 37s 617us/step - loss: 0.1070 - accuracy: 0.9682 -
val_loss: 0.0693 - val_accuracy: 0.9790
Epoch 10/20
60000/60000 [==============================] - 41s 677us/step - loss: 0.1029 - accuracy: 0.9701 -
val_loss: 0.0723 - val_accuracy: 0.9795
Epoch 11/20
60000/60000 [==============================] - 46s 764us/step - loss: 0.0955 - accuracy: 0.9718 -
val_loss: 0.0656 - val_accuracy: 0.9811
Epoch 12/20
60000/60000 [==============================] - 34s 559us/step - loss: 0.0907 - accuracy: 0.9732 -
val_loss: 0.0630 - val_accuracy: 0.9813
Epoch 13/20
60000/60000 [==============================] - 34s 560us/step - loss: 0.0861 - accuracy: 0.9749 -
val_loss: 0.0666 - val_accuracy: 0.9805
Epoch 14/20
60000/60000 [==============================] - 34s 562us/step - loss: 0.0811 - accuracy: 0.9758 -
val_loss: 0.0683 - val_accuracy: 0.9801
Epoch 15/20
60000/60000 [==============================] - 34s 560us/step - loss: 0.0815 - accuracy: 0.9756 -
val_loss: 0.0625 - val_accuracy: 0.9831
Epoch 16/20
60000/60000 [==============================] - 35s 576us/step - loss: 0.0742 - accuracy: 0.9782 -
val_loss: 0.0620 - val_accuracy: 0.9817
Epoch 17/20
60000/60000 [==============================] - 35s 582us/step - loss: 0.0714 - accuracy: 0.9793 -
val_loss: 0.0652 - val_accuracy: 0.9806
Epoch 18/20
60000/60000 [==============================] - 36s 593us/step - loss: 0.0689 - accuracy: 0.9796 -
val_loss: 0.0608 - val_accuracy: 0.9843
Epoch 19/20
60000/60000 [==============================] - 36s 597us/step - loss: 0.0675 - accuracy: 0.9804 -
val_loss: 0.0666 - val_accuracy: 0.9814
Epoch 20/20
60000/60000 [==============================] - 35s 582us/step - loss: 0.0644 - accuracy: 0.9808 -
val_loss: 0.0567 - val_accuracy: 0.9847
```

In [48]:

```
score = model_2.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
```

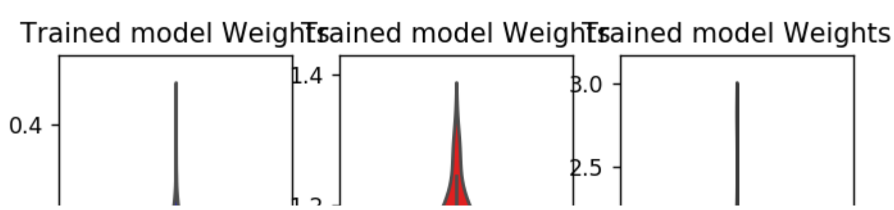
```
vy = history_m2.history['val_loss']
ty = history_m2.history['loss']
plt_dynamic(x, vy, ty, ax)
```

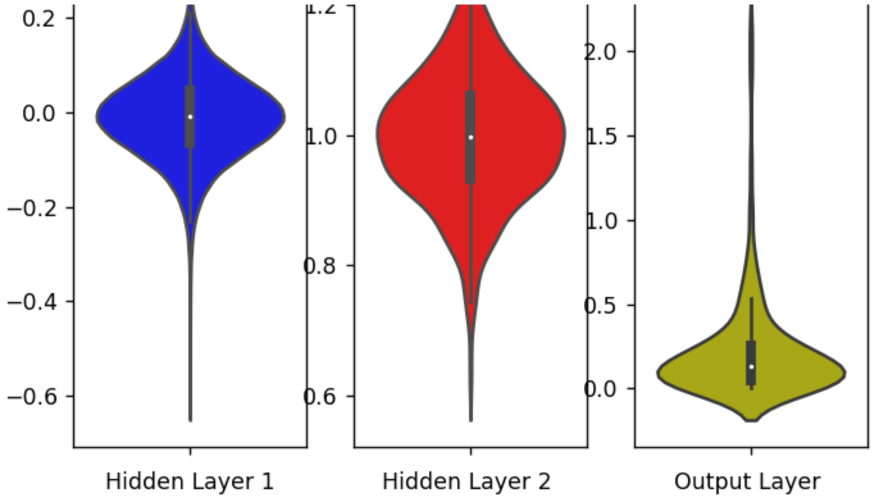
```
Test score: 0.056653810659673766
Test accuracy: 0.9847000241279602
```




In [49]:

```
w_after = model_2.get_weights()

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


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

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

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






## MLP + BN + Dropout(0.2) on 3 hidden Layers

In [51]:

```
from keras.layers.normalization import BatchNormalization
from keras.layers import Dropout

model_32 = Sequential()

model_32.add(Dense(502, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNorma
l(mean=0.0, stddev=0.062, seed=None)))
model_32.add(BatchNormalization())
model_32.add(Dropout(0.2))

model_32.add(Dense(304, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.074,
seed=None)))
model_32.add(BatchNormalization())
model_32.add(Dropout(0.2))

model_32.add(Dense(76, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.185, s
eed=None)) )
model_32.add(BatchNormalization())
model_32.add(Dropout(0.2))

model_32.add(Dense(output_dim, activation='softmax'))


model_32.summary()
```

```
Model: "sequential_17"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_48 (Dense)             (None, 502)               394070
_________________________________________________________________
batch_normalization_10 (Batc (None, 502)               2008
_________________________________________________________________
dropout_8 (Dropout)          (None, 502)               0
_________________________________________________________________
dense_49 (Dense)             (None, 304)               152912
_________________________________________________________________
batch_normalization_11 (Batc (None, 304)               1216
_________________________________________________________________
dropout_9 (Dropout)          (None, 304)               0
_________________________________________________________________
dense_50 (Dense)             (None, 76)                23180
_________________________________________________________________
batch_normalization_12 (Batc (None, 76)                304
_________________________________________________________________
dropout_10 (Dropout)         (None, 76)                0
_________________________________________________________________
dense_51 (Dense)             (None, 10)                770
=================================================================
```

```
Total params: 574,460
Trainable params: 572,696
Non-trainable params: 1,764
_________________________________________________________________
```

In [52]:

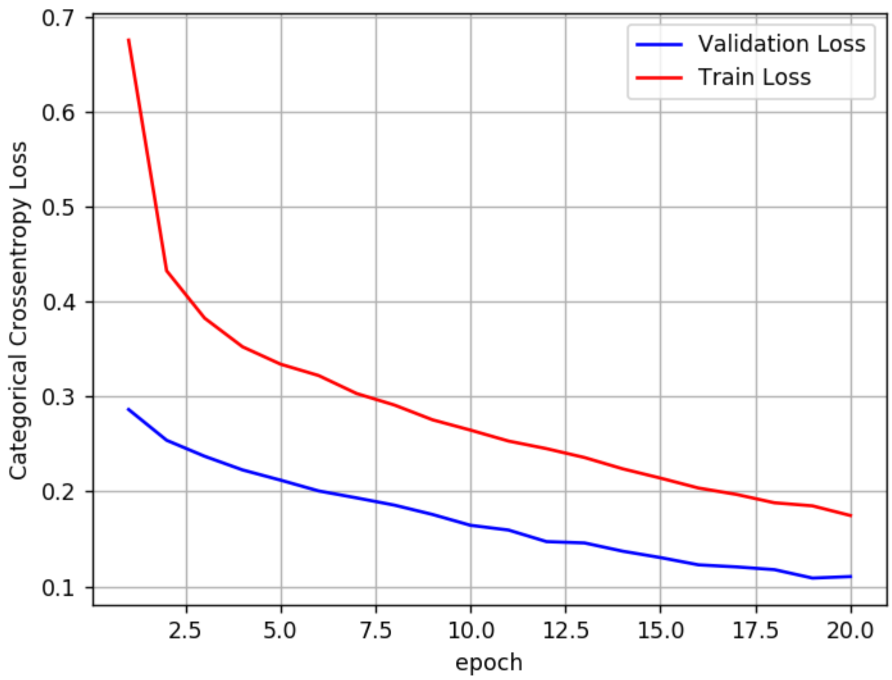
```
model_32.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history_32 = model_32.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 [==============================] - 43s 712us/step - loss: 0.3052 - accuracy: 0.9086 -
val_loss: 0.1177 - val_accuracy: 0.9642
Epoch 2/20
60000/60000 [==============================] - 36s 606us/step - loss: 0.1305 - accuracy: 0.9612 -
val_loss: 0.0879 - val_accuracy: 0.9724
Epoch 3/20
60000/60000 [==============================] - 37s 612us/step - loss: 0.0944 - accuracy: 0.9702 -
val_loss: 0.0840 - val_accuracy: 0.9730
Epoch 4/20
60000/60000 [==============================] - 39s 657us/step - loss: 0.0776 - accuracy: 0.9760 -
val_loss: 0.0707 - val_accuracy: 0.9768
Epoch 5/20
60000/60000 [==============================] - 41s 684us/step - loss: 0.0656 - accuracy: 0.9793 -
val_loss: 0.0700 - val_accuracy: 0.9777
Epoch 6/20
60000/60000 [==============================] - 39s 647us/step - loss: 0.0567 - accuracy: 0.9815 -
val_loss: 0.0685 - val_accuracy: 0.9791
Epoch 7/20
60000/60000 [==============================] - 38s 640us/step - loss: 0.0504 - accuracy: 0.9843 -
val_loss: 0.0667 - val_accuracy: 0.9795
Epoch 8/20
60000/60000 [==============================] - 38s 636us/step - loss: 0.0477 - accuracy: 0.9853 -
val_loss: 0.0580 - val_accuracy: 0.9812
Epoch 9/20
60000/60000 [==============================] - 39s 648us/step - loss: 0.0414 - accuracy: 0.9867 -
val_loss: 0.0575 - val_accuracy: 0.9821
Epoch 10/20
60000/60000 [==============================] - 37s 621us/step - loss: 0.0386 - accuracy: 0.9876 -
val_loss: 0.0542 - val_accuracy: 0.9828
Epoch 11/20
60000/60000 [==============================] - 37s 622us/step - loss: 0.0346 - accuracy: 0.9884 -
val_loss: 0.0573 - val_accuracy: 0.9836
Epoch 12/20
60000/60000 [==============================] - 38s 632us/step - loss: 0.0324 - accuracy: 0.9895 -
val_loss: 0.0587 - val_accuracy: 0.9832
Epoch 13/20
60000/60000 [==============================] - 38s 637us/step - loss: 0.0307 - accuracy: 0.9897 -
val_loss: 0.0582 - val_accuracy: 0.9839
Epoch 14/20
60000/60000 [==============================] - 39s 644us/step - loss: 0.0293 - accuracy: 0.9904 -
val_loss: 0.0545 - val_accuracy: 0.9844
Epoch 15/20
60000/60000 [==============================] - 40s 669us/step - loss: 0.0273 - accuracy: 0.9912 -
val_loss: 0.0583 - val_accuracy: 0.9838
Epoch 16/20
60000/60000 [==============================] - 41s 679us/step - loss: 0.0263 - accuracy: 0.9911 -
val_loss: 0.0674 - val_accuracy: 0.9801
Epoch 17/20
60000/60000 [==============================] - 37s 612us/step - loss: 0.0234 - accuracy: 0.9923 -
val_loss: 0.0599 - val_accuracy: 0.9837
Epoch 18/20
60000/60000 [==============================] - 33s 548us/step - loss: 0.0251 - accuracy: 0.9916 -
val_loss: 0.0707 - val_accuracy: 0.9800
Epoch 19/20
60000/60000 [==============================] - 32s 540us/step - loss: 0.0219 - accuracy: 0.9929 -
val_loss: 0.0632 - val_accuracy: 0.9823
Epoch 20/20
60000/60000 [==============================] - 33s 551us/step - loss: 0.0227 - accuracy: 0.9926 -
val_loss: 0.0627 - val_accuracy: 0.9826
```

In [53]:

```
score = model_32.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)
```

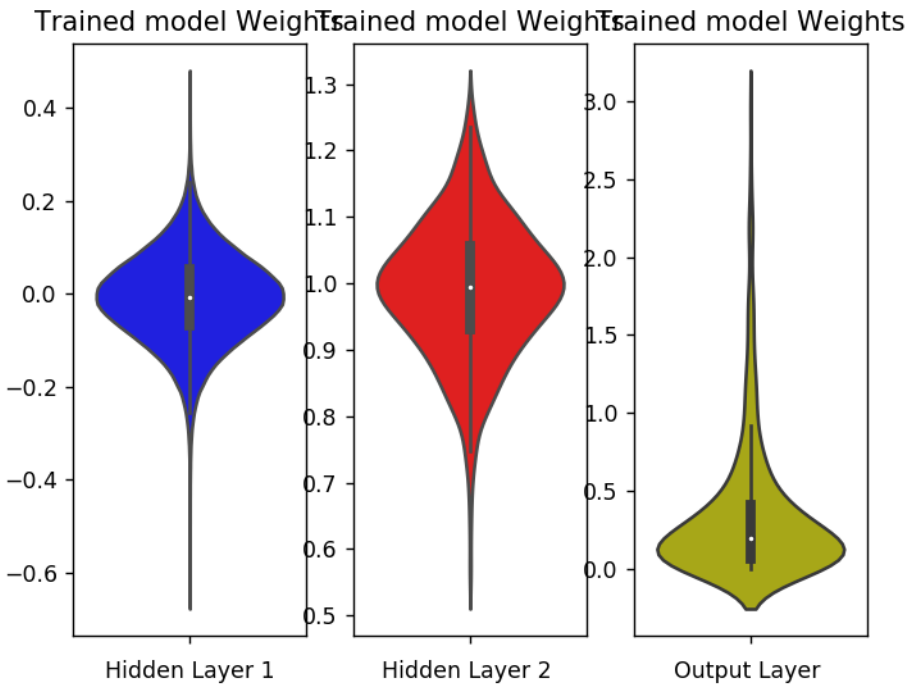
```
Test score: 0.06272427673040802
Test accuracy: 0.9825999736785889
```




In [54]:

```
w_after = model_32.get_weights()

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


fig = plt.figure()
plt.title("Weight matrices after model trained")
plt.subplot(1, 3, 1)
plt.title("Trained model Weights")
```

```
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

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

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




## MLP + ReLu + Adam+ BN+Dropout(0.5) + 5-Layer(512,364,256,128,64)

In [55]:

```
# Initialising model
model_3 = Sequential()

# first hidden layer
model_3.add(Dense(512, activation='relu', input_shape=(input_dim,), kernel_initializer=he_normal(se
ed=None)))
model_3.add(BatchNormalization())
model_3.add(Dropout(0.5))

# second hidden layer
model_3.add(Dense(364, activation='relu', kernel_initializer=he_normal(seed=None)))
model_3.add(BatchNormalization())
model_3.add(Dropout(0.5))

# third hidden layer
model_3.add(Dense(256, activation='relu', kernel_initializer=he_normal(seed=None)))
model_3.add(BatchNormalization())
model_3.add(Dropout(0.5))

# fourth hidden layer
model_3.add(Dense(128, activation='relu', kernel_initializer=he_normal(seed=None)))
model_3.add(BatchNormalization())
model_3.add(Dropout(0.5))

# fifth hidden layer
model_3.add(Dense(64, activation='relu', kernel_initializer=he_normal(seed=None)))
model_3.add(BatchNormalization())
```

```
model_3.add(BatchNormalization())
model_3.add(Dropout(0.5))

# Adding output layer
model_3.add(Dense(output_dim, activation='softmax'))


model_3.summary()
```

```
Model: "sequential_18"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_52 (Dense)             (None, 512)               401920    
_________________________________________________________________
batch_normalization_13 (Batc (None, 512)               2048      
_________________________________________________________________
dropout_11 (Dropout)         (None, 512)               0         
_________________________________________________________________
dense_53 (Dense)             (None, 364)               186732    
_________________________________________________________________
batch_normalization_14 (Batc (None, 364)               1456      
_________________________________________________________________
dropout_12 (Dropout)         (None, 364)               0         
_________________________________________________________________
dense_54 (Dense)             (None, 256)               93440     
_________________________________________________________________
batch_normalization_15 (Batc (None, 256)               1024      
_________________________________________________________________
dropout_13 (Dropout)         (None, 256)               0         
_________________________________________________________________
dense_55 (Dense)             (None, 128)               32896     
_________________________________________________________________
batch_normalization_16 (Batc (None, 128)               512       
_________________________________________________________________
dropout_14 (Dropout)         (None, 128)               0         
_________________________________________________________________
dense_56 (Dense)             (None, 64)                8256      
_________________________________________________________________
batch_normalization_17 (Batc (None, 64)                256       
_________________________________________________________________
dropout_15 (Dropout)         (None, 64)                0         
_________________________________________________________________
dense_57 (Dense)             (None, 10)                650       
=================================================================
Total params: 729,190
Trainable params: 726,542
Non-trainable params: 2,648
_________________________________________________________________
```

In [56]:

```
model_3.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history_m3= model_3.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, valida
tion_data=(X_test, Y_test))
```

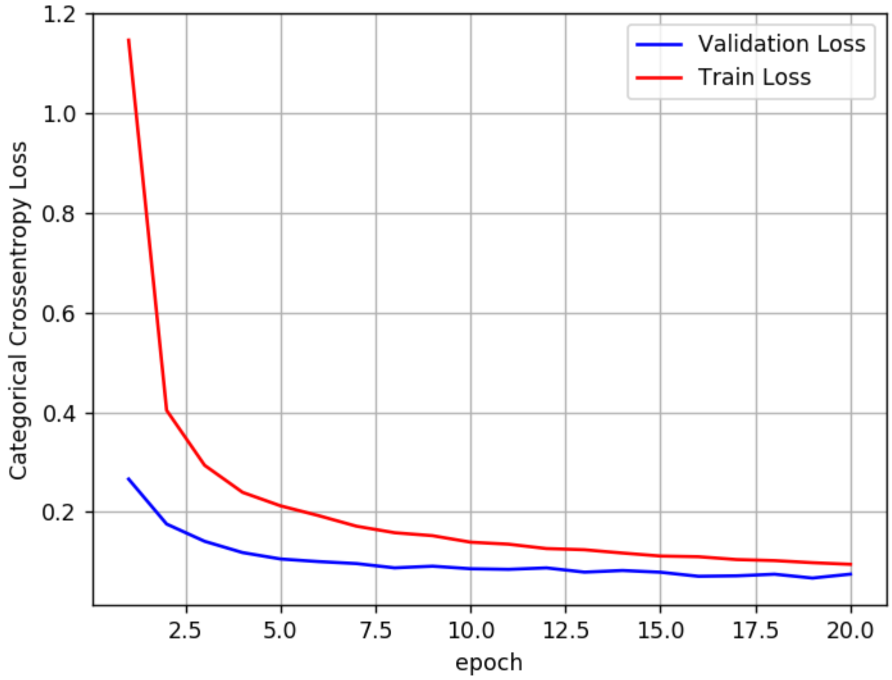
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 49s 811us/step - loss: 1.1462 - accuracy: 0.6388 - 
val_loss: 0.2659 - val_accuracy: 0.9249
Epoch 2/20
60000/60000 [==============================] - 58s 968us/step - loss: 0.4038 - accuracy: 0.8872 - 
val_loss: 0.1757 - val_accuracy: 0.9524
Epoch 3/20
60000/60000 [==============================] - 44s 730us/step - loss: 0.2936 - accuracy: 0.9221 - 
val_loss: 0.1411 - val_accuracy: 0.9619
Epoch 4/20
60000/60000 [==============================] - 42s 706us/step - loss: 0.2393 - accuracy: 0.9372 - 
val_loss: 0.1185 - val_accuracy: 0.9683
Epoch 5/20
60000/60000 [==============================] - 44s 728us/step - loss: 0.2122 - accuracy: 0.9443 - 
val_loss: 0.1057 - val_accuracy: 0.9724
Epoch 6/20
60000/60000 [==============================] - 42s 702us/step - loss: 0.1926 - accuracy: 0.9498 - 
```

```
val_loss: 0.1005 - val_accuracy: 0.9722
Epoch 7/20
60000/60000 [==============================] - 42s 703us/step - loss: 0.1714 - accuracy: 0.9553 -
val_loss: 0.0965 - val_accuracy: 0.9750
Epoch 8/20
60000/60000 [==============================] - 50s 836us/step - loss: 0.1584 - accuracy: 0.9588 -
val_loss: 0.0879 - val_accuracy: 0.9767
Epoch 9/20
60000/60000 [==============================] - 54s 892us/step - loss: 0.1524 - accuracy: 0.9606 -
val_loss: 0.0913 - val_accuracy: 0.9773
Epoch 10/20
60000/60000 [==============================] - 52s 872us/step - loss: 0.1394 - accuracy: 0.9638 -
val_loss: 0.0861 - val_accuracy: 0.9769
Epoch 11/20
60000/60000 [==============================] - 17s 285us/step - loss: 0.1354 - accuracy: 0.9633 -
val_loss: 0.0849 - val_accuracy: 0.9779
Epoch 12/20
60000/60000 [==============================] - 14s 232us/step - loss: 0.1266 - accuracy: 0.9674 -
val_loss: 0.0878 - val_accuracy: 0.9776
Epoch 13/20
60000/60000 [==============================] - 14s 229us/step - loss: 0.1242 - accuracy: 0.9676 -
val_loss: 0.0793 - val_accuracy: 0.9791
Epoch 14/20
60000/60000 [==============================] - 14s 229us/step - loss: 0.1176 - accuracy: 0.9690 -
val_loss: 0.0826 - val_accuracy: 0.9792
Epoch 15/20
60000/60000 [==============================] - 14s 232us/step - loss: 0.1116 - accuracy: 0.9712 -
val_loss: 0.0791 - val_accuracy: 0.9804
Epoch 16/20
60000/60000 [==============================] - 14s 231us/step - loss: 0.1102 - accuracy: 0.9713 -
val_loss: 0.0710 - val_accuracy: 0.9826
Epoch 17/20
60000/60000 [==============================] - 19s 319us/step - loss: 0.1046 - accuracy: 0.9724 -
val_loss: 0.0719 - val_accuracy: 0.9815
Epoch 18/20
60000/60000 [==============================] - 22s 363us/step - loss: 0.1025 - accuracy: 0.9736 -
val_loss: 0.0752 - val_accuracy: 0.9820
Epoch 19/20
60000/60000 [==============================] - 22s 368us/step - loss: 0.0982 - accuracy: 0.9741 -
val_loss: 0.0674 - val_accuracy: 0.9833
Epoch 20/20
60000/60000 [==============================] - 22s 365us/step - loss: 0.0950 - accuracy: 0.9754 -
val_loss: 0.0753 - val_accuracy: 0.9823
```

In [57]:

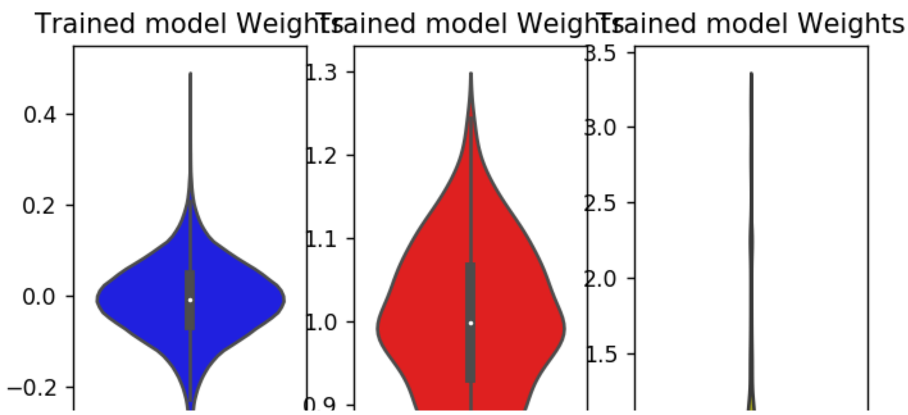
```
score = model_3.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

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_m3.history['val_loss']
ty = history_m3.history['loss']
plt_dynamic(x, vy, ty, ax)
```

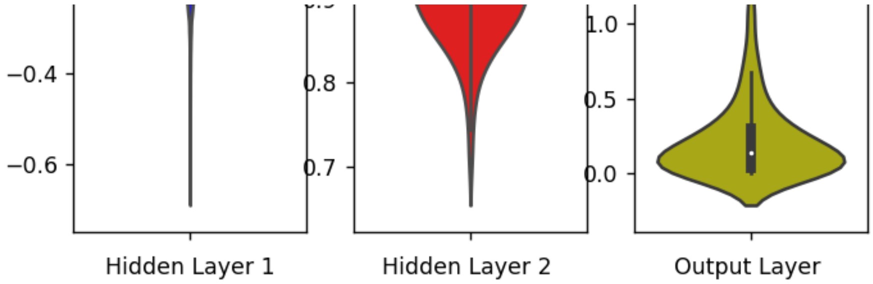
```
Test score: 0.07529761268235743
Test accuracy: 0.9822999835014343
```




In [58]:

```
w_after = model_3.get_weights()

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


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

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

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






# MLP + ReLu + Adam+ BN+Dropout(0.2) + 5-Layer(612,464,311,158,78)

In [59]:

```
from keras.layers.normalization import BatchNormalization
from keras.layers import Dropout

model_52 = Sequential()

model_52.add(Dense(612, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNorma
l(mean=0.0, stddev=0.054, seed=None)))
model_52.add(BatchNormalization())
model_52.add(Dropout(0.2))

model_52.add(Dense(464, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.066,
seed=None)))
model_52.add(BatchNormalization())
model_52.add(Dropout(0.2))

model_52.add(Dense(311, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.080,
seed=None)))
model_52.add(BatchNormalization())
model_52.add(Dropout(0.2))

model_52.add(Dense(158, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.088,
seed=None)))
model_52.add(BatchNormalization())
model_52.add(Dropout(0.2))

model_52.add(Dense(78, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.125, s
eed=None)) )
model_52.add(BatchNormalization())
model_52.add(Dropout(0.2))


model_52.add(Dense(output_dim, activation='softmax'))


model_52.summary()
```

```
Model: "sequential_19"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_58 (Dense)             (None, 612)               480420
_________________________________________________________________
batch_normalization_18 (Batc (None, 612)               2448
_________________________________________________________________
dropout_16 (Dropout)         (None, 612)               0
_________________________________________________________________
dense_59 (Dense)             (None, 464)               284432
_________________________________________________________________
batch_normalization_19 (Batc (None, 464)               1856
_________________________________________________________________
dropout_17 (Dropout)         (None, 464)               0
_________________________________________________________________
dense_60 (Dense)             (None, 311)               144615
_________________________________________________________________
batch_normalization_20 (Batc (None, 311)               1244
```

```
_________________________________________________________________
dropout_18 (Dropout)         (None, 311)               0
_________________________________________________________________
dense_61 (Dense)             (None, 158)               49296
_________________________________________________________________
batch_normalization_21 (Batc (None, 158)               632
_________________________________________________________________
dropout_19 (Dropout)         (None, 158)               0
_________________________________________________________________
dense_62 (Dense)             (None, 78)                12402
_________________________________________________________________
batch_normalization_22 (Batc (None, 78)                312
_________________________________________________________________
dropout_20 (Dropout)         (None, 78)                0
_________________________________________________________________
dense_63 (Dense)             (None, 10)                790
=================================================================
Total params: 978,447
Trainable params: 975,201
Non-trainable params: 3,246
_________________________________________________________________
```

In [60]:

```
model_52.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history_52 = model_52.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 [==============================] - 24s 400us/step - loss: 0.3608 - accuracy: 0.8925 -
val_loss: 0.1296 - val_accuracy: 0.9608
Epoch 2/20
60000/60000 [==============================] - 22s 363us/step - loss: 0.1464 - accuracy: 0.9560 -
val_loss: 0.1057 - val_accuracy: 0.9705
Epoch 3/20
60000/60000 [==============================] - 21s 357us/step - loss: 0.1109 - accuracy: 0.9668 -
val_loss: 0.0842 - val_accuracy: 0.9754
Epoch 4/20
60000/60000 [==============================] - 22s 369us/step - loss: 0.0893 - accuracy: 0.9728 -
val_loss: 0.0757 - val_accuracy: 0.9773
Epoch 5/20
60000/60000 [==============================] - 22s 375us/step - loss: 0.0769 - accuracy: 0.9759 -
val_loss: 0.0806 - val_accuracy: 0.9751
Epoch 6/20
60000/60000 [==============================] - 22s 369us/step - loss: 0.0684 - accuracy: 0.9794 -
val_loss: 0.0657 - val_accuracy: 0.9804
Epoch 7/20
60000/60000 [==============================] - 26s 435us/step - loss: 0.0646 - accuracy: 0.9799 -
val_loss: 0.0644 - val_accuracy: 0.9823
Epoch 8/20
60000/60000 [==============================] - 35s 575us/step - loss: 0.0555 - accuracy: 0.9825 -
val_loss: 0.0746 - val_accuracy: 0.9797
Epoch 9/20
60000/60000 [==============================] - 35s 586us/step - loss: 0.0540 - accuracy: 0.9835 -
val_loss: 0.0776 - val_accuracy: 0.9796
Epoch 10/20
60000/60000 [==============================] - 35s 579us/step - loss: 0.0501 - accuracy: 0.9846 -
val_loss: 0.0666 - val_accuracy: 0.9818
Epoch 11/20
60000/60000 [==============================] - 28s 466us/step - loss: 0.0433 - accuracy: 0.9860 -
val_loss: 0.0643 - val_accuracy: 0.9821
Epoch 12/20
60000/60000 [==============================] - 20s 331us/step - loss: 0.0439 - accuracy: 0.9860 -
val_loss: 0.0647 - val_accuracy: 0.9813
Epoch 13/20
60000/60000 [==============================] - 21s 345us/step - loss: 0.0374 - accuracy: 0.9880 -
val_loss: 0.0742 - val_accuracy: 0.9789
Epoch 14/20
60000/60000 [==============================] - 20s 328us/step - loss: 0.0363 - accuracy: 0.9884 -
val_loss: 0.0690 - val_accuracy: 0.9829
Epoch 15/20
60000/60000 [==============================] - 20s 334us/step - loss: 0.0347 - accuracy: 0.9892 -
val_loss: 0.0581 - val_accuracy: 0.9838
Epoch 16/20
```

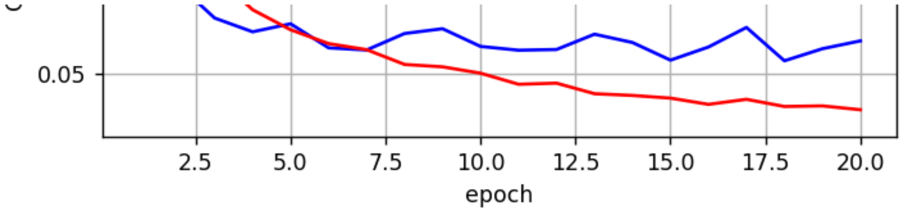
```
60000/60000 [==============================] - 21s 344us/step - loss: 0.0308 - accuracy: 0.9904 - val_loss: 0.0663 - val_accuracy: 0.9820
Epoch 17/20
60000/60000 [==============================] - 20s 337us/step - loss: 0.0340 - accuracy: 0.9896 - val_loss: 0.0784 - val_accuracy: 0.9805
Epoch 18/20
60000/60000 [==============================] - 22s 358us/step - loss: 0.0295 - accuracy: 0.9906 - val_loss: 0.0578 - val_accuracy: 0.9841
Epoch 19/20
60000/60000 [==============================] - 20s 331us/step - loss: 0.0299 - accuracy: 0.9901 - val_loss: 0.0652 - val_accuracy: 0.9824
Epoch 20/20
60000/60000 [==============================] - 20s 335us/step - loss: 0.0275 - accuracy: 0.9916 - val_loss: 0.0701 - val_accuracy: 0.9831
```

In [61]:

```
score = model_52.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, validation_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_52.history['val_loss']
ty = history_52.history['loss']
plt_dynamic(x, vy, ty, ax)
```

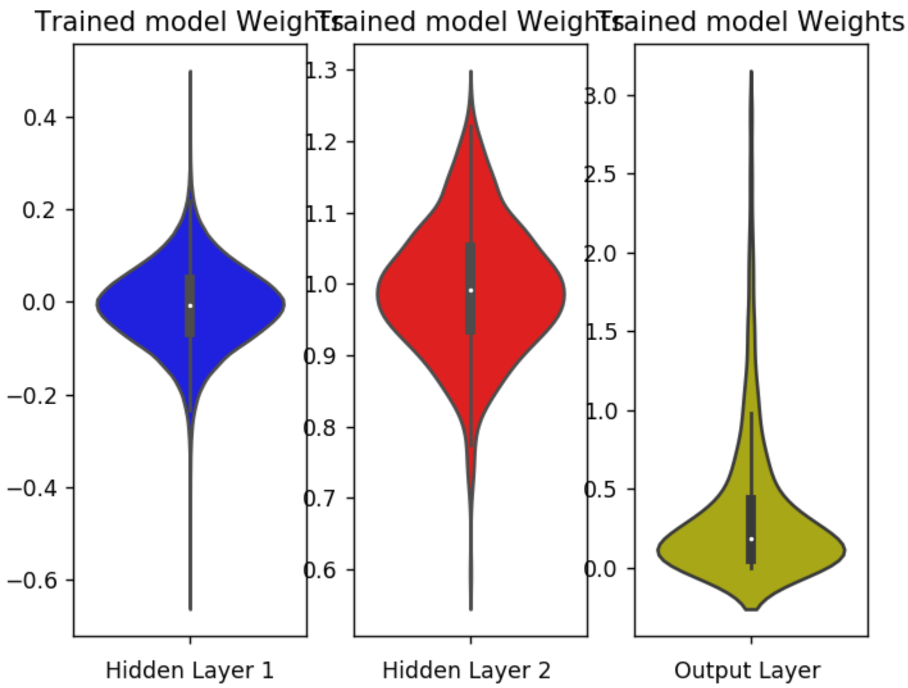
```
Test score: 0.07005564393560634
Test accuracy: 0.9830999970436096
```

```
C:\Users\Santosh\Anaconda3\lib\site-packages\matplotlib\pyplot.py:514: RuntimeWarning: More than 20 figures have been opened. Figures created through the pyplot interface (`matplotlib.pyplot.figure`) are retained until explicitly closed and may consume too much memory. (To control this warning, see the rcParam `figure.max_open_warning`).
  max_open_warning, RuntimeWarning)
```




In [62]:

```
w_after = model_52.get_weights()

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


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

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

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




In [ ]:

```

```

In [ ]:

```

```

## Conclusion

In [63]:

```
from prettytable import PrettyTable

x = PrettyTable()

x.field_names = ["Model","Test loss", "Test accuracy"]
x.add_row(["MLP + ReLu activation + Adam Optimizer + BN+Dropout(0.5)+ 2-Hidden Layer",
0.06056223605640116,0.9824000000953674])

x.add_row(["MLP + ReLu activation + Adam Optimizer + BN+Dropout(0.2)+ 2-Hidden Layer",
0.06859428682197286,0.983299970626831])

x.add_row(["MLP + ReLu activation + Adam Optimizer + BN+Dropout(0.5)+ 3-Hidden Layer",
0.06358614531699568,0.9828000068664551])

x.add_row(["MLP + ReLu activation + Adam Optimizer + BN+Dropout(0.2)+ 3-Hidden Layer",
0.06272427673040802,0.9825999736785889])

x.add_row(["MLP + ReLu activation + Adam Optimizer + BN+Dropout(0.5)+ 5-Hidden Layer",
0.07726619798289612,0.9807999730110168])

x.add_row(["MLP + ReLu activation + Adam Optimizer + BN+Dropout(0.2)+ 5-Hidden Layer",
0.07005564393560634,0.9830999970436096])

print(x)
```

```
+---------------------------------------------------------------------------+---------------------+-
---------------+
|                                   Model                                   |      Test loss      |
est accuracy    |
+---------------------------------------------------------------------------+---------------------+-
---------------+
| MLP + ReLu activation + Adam Optimizer + BN+Dropout(0.5)+ 2-Hidden Layer | 0.06056223605640116 |
0.9824000000953674 |
| MLP + ReLu activation + Adam Optimizer + BN+Dropout(0.2)+ 2-Hidden Layer | 0.06859428682197286 |
0.983299970626831  |
| MLP + ReLu activation + Adam Optimizer + BN+Dropout(0.5)+ 3-Hidden Layer | 0.06358614531699568 |
0.9828000068664551 |
| MLP + ReLu activation + Adam Optimizer + BN+Dropout(0.2)+ 3-Hidden Layer | 0.06272427673040802 |
0.9825999736785889 |
| MLP + ReLu activation + Adam Optimizer + BN+Dropout(0.5)+ 5-Hidden Layer | 0.07726619798289612 |
0.9807999730110168 |
| MLP + ReLu activation + Adam Optimizer + BN+Dropout(0.2)+ 5-Hidden Layer | 0.07005564393560634 |
0.9830999970436096 |
+---------------------------------------------------------------------------+---------------------+-
---------------+
```

In [ ]:

In [ ]: