Keras -- MLPs on MNIST

In [0]:

```
# 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
```

In [0]:

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

In [0]:

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

In [80]:

```
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 [0]:

```
# 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 [82]:

```
# 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 [83]:

```
# 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 [0]:

```
# 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 [85]:

```
# 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 [86]:

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

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

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

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

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

Softmax classifier

In [0]:

```
# 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'),
```

```
#     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 [0]:

```
# some model parameters

output_dim = 10
input_dim = X_train.shape[1]

batch_size = 128
nb_epoch = 20
```

MLP + Relu activation + ADAM with 2 hidden layers

In [89]:

```
# Multilayer perceptron

model_relu = Sequential()
model_relu.add(Dense(392, activation='relu', input_shape=(input_dim,)))
model_relu.add(Dense(196, activation='relu'))
model_relu.add(Dense(output_dim, activation='softmax'))

model_relu.summary()
```

```
Model: "sequential_20"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_80 (Dense)             (None, 392)               307720
```

```
dense_80 (Dense)             (None, 392)               307720
_________________________________________________________________
dense_81 (Dense)             (None, 196)               77028
_________________________________________________________________
dense_82 (Dense)             (None, 10)                1970
=================================================================
Total params: 386,718
Trainable params: 386,718
Non-trainable params: 0
_________________________________________________________________
```

In [90]:

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

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

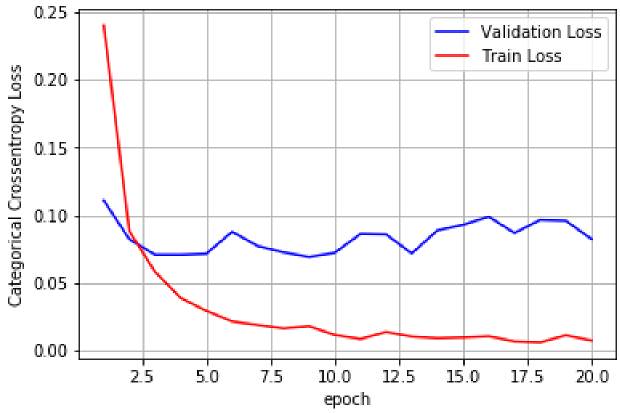
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 6s 100us/step - loss: 0.2401 - acc: 0.9304 -
val_loss: 0.1109 - val_acc: 0.9654
Epoch 2/20
60000/60000 [==============================] - 3s 53us/step - loss: 0.0881 - acc: 0.9730 -
val_loss: 0.0822 - val_acc: 0.9752
Epoch 3/20
60000/60000 [==============================] - 3s 53us/step - loss: 0.0581 - acc: 0.9822 -
val_loss: 0.0708 - val_acc: 0.9787
Epoch 4/20
60000/60000 [==============================] - 3s 53us/step - loss: 0.0388 - acc: 0.9879 -
val_loss: 0.0707 - val_acc: 0.9793
Epoch 5/20
60000/60000 [==============================] - 3s 53us/step - loss: 0.0294 - acc: 0.9905 -
val_loss: 0.0715 - val_acc: 0.9777
Epoch 6/20
60000/60000 [==============================] - 3s 53us/step - loss: 0.0215 - acc: 0.9932 -
val_loss: 0.0878 - val_acc: 0.9750
Epoch 7/20
60000/60000 [==============================] - 3s 53us/step - loss: 0.0189 - acc: 0.9942 -
val_loss: 0.0772 - val_acc: 0.9795
Epoch 8/20
60000/60000 [==============================] - 3s 53us/step - loss: 0.0164 - acc: 0.9947 -
val_loss: 0.0725 - val_acc: 0.9813
Epoch 9/20
60000/60000 [==============================] - 3s 54us/step - loss: 0.0180 - acc: 0.9941 -
val_loss: 0.0691 - val_acc: 0.9817
Epoch 10/20
60000/60000 [==============================] - 3s 53us/step - loss: 0.0115 - acc: 0.9961 -
val_loss: 0.0722 - val_acc: 0.9822
Epoch 11/20
60000/60000 [==============================] - 3s 54us/step - loss: 0.0085 - acc: 0.9975 -
val_loss: 0.0861 - val_acc: 0.9810
Epoch 12/20
60000/60000 [==============================] - 3s 53us/step - loss: 0.0137 - acc: 0.9957 -
val_loss: 0.0858 - val_acc: 0.9795
Epoch 13/20
60000/60000 [==============================] - 3s 54us/step - loss: 0.0103 - acc: 0.9966 -
val_loss: 0.0717 - val_acc: 0.9833
Epoch 14/20
60000/60000 [==============================] - 3s 53us/step - loss: 0.0091 - acc: 0.9971 -
val_loss: 0.0888 - val_acc: 0.9801
Epoch 15/20
60000/60000 [==============================] - 3s 53us/step - loss: 0.0097 - acc: 0.9969 -
val_loss: 0.0929 - val_acc: 0.9794
Epoch 16/20
60000/60000 [==============================] - 3s 53us/step - loss: 0.0106 - acc: 0.9965 -
val_loss: 0.0988 - val_acc: 0.9791
Epoch 17/20
60000/60000 [==============================] - 3s 52us/step - loss: 0.0067 - acc: 0.9978 -
val_loss: 0.0868 - val_acc: 0.9824
Epoch 18/20
60000/60000 [==============================] - 3s 53us/step - loss: 0.0060 - acc: 0.9980 -
val_loss: 0.0964 - val_acc: 0.9806
Epoch 19/20
60000/60000 [==============================] - 3s 53us/step - loss: 0.0113 - acc: 0.9964 -
val_loss: 0.0958 - val_acc: 0.9809
```

```
Epoch 20/20
60000/60000 [==============================] - 3s 53us/step - loss: 0.0074 - acc: 0.9978 -
val_loss: 0.0824 - val_acc: 0.9832
```

In [91]:

```
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)
```

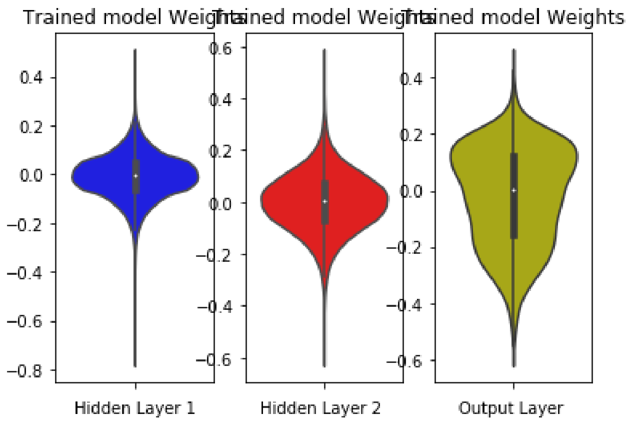
```
Test score: 0.08238437657678974
Test accuracy: 0.9832
```



In [92]:

```
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 activation + ADAM + Batch Normalization with 2 hidden layers

In [94]:

```
# Multilayer perceptron
from keras.layers.normalization import BatchNormalization
model_relu = Sequential()
model_relu.add(Dense(392, activation='relu', input_shape=(input_dim,)))
model_relu.add(BatchNormalization())
model_relu.add(Dense(196, activation='relu'))
model_relu.add(BatchNormalization())
model_relu.add(Dense(output_dim, activation='softmax'))

model_relu.summary()
```

```
Model: "sequential_22"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_86 (Dense)             (None, 392)               307720
_________________________________________________________________
batch_normalization_32 (Batc (None, 392)               1568
_________________________________________________________________
dense_87 (Dense)             (None, 196)               77028
_________________________________________________________________
batch_normalization_33 (Batc (None, 196)               784
_________________________________________________________________
dense_88 (Dense)             (None, 10)                1970
=================================================================
Total params: 389,070
Trainable params: 387,894
Non-trainable params: 1,176
_________________________________________________________________
```

In [95]:

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

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

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 8s 139us/step - loss: 0.1823 - acc: 0.9451 -
val_loss: 0.0967 - val_acc: 0.9684
Epoch 2/20
60000/60000 [==============================] - 5s 83us/step - loss: 0.0722 - acc: 0.9776 -
val_loss: 0.0856 - val_acc: 0.9706
Epoch 3/20
```

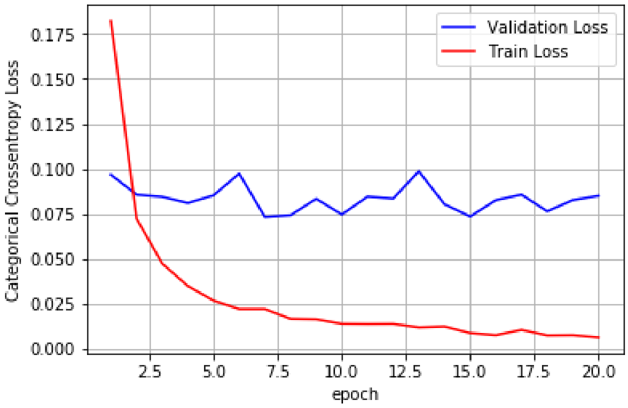
```
60000/60000 [==============================] - 5s 88us/step - loss: 0.0473 - acc: 0.9853 -
val_loss: 0.0844 - val_acc: 0.9756
Epoch 4/20
60000/60000 [==============================] - 5s 85us/step - loss: 0.0347 - acc: 0.9886 -
val_loss: 0.0809 - val_acc: 0.9756
Epoch 5/20
60000/60000 [==============================] - 5s 83us/step - loss: 0.0266 - acc: 0.9918 -
val_loss: 0.0852 - val_acc: 0.9759
Epoch 6/20
60000/60000 [==============================] - 5s 86us/step - loss: 0.0219 - acc: 0.9928 -
val_loss: 0.0974 - val_acc: 0.9721
Epoch 7/20
60000/60000 [==============================] - 5s 85us/step - loss: 0.0219 - acc: 0.9925 -
val_loss: 0.0731 - val_acc: 0.9787
Epoch 8/20
60000/60000 [==============================] - 5s 85us/step - loss: 0.0164 - acc: 0.9945 -
val_loss: 0.0741 - val_acc: 0.9793
Epoch 9/20
60000/60000 [==============================] - 5s 83us/step - loss: 0.0162 - acc: 0.9945 -
val_loss: 0.0833 - val_acc: 0.9788
Epoch 10/20
60000/60000 [==============================] - 5s 85us/step - loss: 0.0137 - acc: 0.9953 -
val_loss: 0.0745 - val_acc: 0.9776
Epoch 11/20
60000/60000 [==============================] - 5s 84us/step - loss: 0.0136 - acc: 0.9954 -
val_loss: 0.0845 - val_acc: 0.9782
Epoch 12/20
60000/60000 [==============================] - 5s 87us/step - loss: 0.0136 - acc: 0.9953 -
val_loss: 0.0834 - val_acc: 0.9797
Epoch 13/20
60000/60000 [==============================] - 5s 86us/step - loss: 0.0117 - acc: 0.9958 -
val_loss: 0.0986 - val_acc: 0.9749
Epoch 14/20
60000/60000 [==============================] - 5s 87us/step - loss: 0.0122 - acc: 0.9961 -
val_loss: 0.0802 - val_acc: 0.9813
Epoch 15/20
60000/60000 [==============================] - 5s 88us/step - loss: 0.0085 - acc: 0.9972 -
val_loss: 0.0734 - val_acc: 0.9819
Epoch 16/20
60000/60000 [==============================] - 5s 86us/step - loss: 0.0073 - acc: 0.9974 -
val_loss: 0.0825 - val_acc: 0.9819
Epoch 17/20
60000/60000 [==============================] - 5s 90us/step - loss: 0.0103 - acc: 0.9968 -
val_loss: 0.0856 - val_acc: 0.9797
Epoch 18/20
60000/60000 [==============================] - 5s 86us/step - loss: 0.0072 - acc: 0.9977 -
val_loss: 0.0763 - val_acc: 0.9825
Epoch 19/20
60000/60000 [==============================] - 5s 86us/step - loss: 0.0073 - acc: 0.9975 -
val_loss: 0.0826 - val_acc: 0.9797
Epoch 20/20
60000/60000 [==============================] - 5s 90us/step - loss: 0.0061 - acc: 0.9982 -
val_loss: 0.0850 - val_acc: 0.9826
```

In [96]:

```
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
```

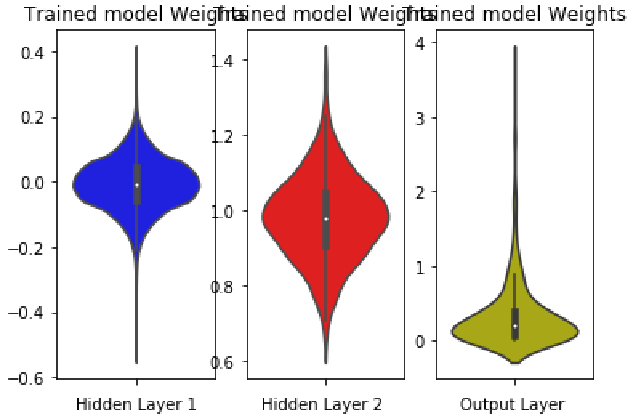
```
# acc : train accuracy
# for each key in histrory.histrory we will have a list of length equal to number of epochs

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

```
Test score: 0.08495574688926236
Test accuracy: 0.9826
```



In [97]:

```
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 activation + ADAM + Dropout with 2 hidden layers

In [98]:

```
# Multilayer perceptron
from keras.layers import Dropout
model_relu = Sequential()
model_relu.add(Dense(392, activation='relu', input_shape=(input_dim,)))
model_relu.add(Dropout(0.5))
model_relu.add(Dense(196, activation='relu'))
model_relu.add(Dropout(0.5))
model_relu.add(Dense(output_dim, activation='softmax'))

model_relu.summary()
```

```
Model: "sequential_23"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_89 (Dense)             (None, 392)               307720
_________________________________________________________________
dropout_27 (Dropout)         (None, 392)               0
_________________________________________________________________
dense_90 (Dense)             (None, 196)               77028
_________________________________________________________________
dropout_28 (Dropout)         (None, 196)               0
_________________________________________________________________
dense_91 (Dense)             (None, 10)                1970
=================================================================
Total params: 386,718
Trainable params: 386,718
Non-trainable params: 0
_________________________________________________________________
```

In [99]:

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

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

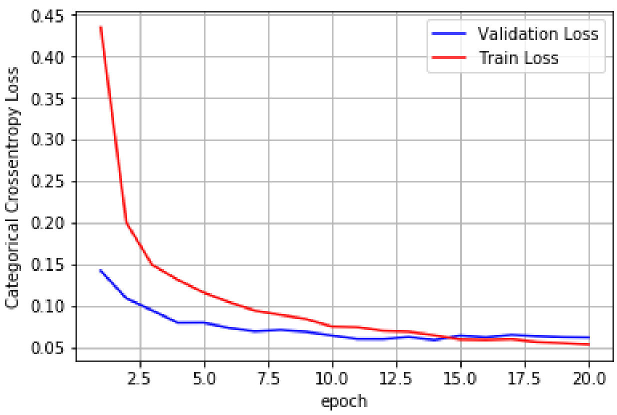
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 7s 109us/step - loss: 0.4348 - acc: 0.8656 -
val_loss: 0.1421 - val_acc: 0.9565
Epoch 2/20
60000/60000 [==============================] - 3s 58us/step - loss: 0.2000 - acc: 0.9408 -
val_loss: 0.1090 - val_acc: 0.9655
Epoch 3/20
60000/60000 [==============================] - 3s 58us/step - loss: 0.1494 - acc: 0.9550 -
val_loss: 0.0946 - val_acc: 0.9688
Epoch 4/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.1313 - acc: 0.9604 -
val_loss: 0.0796 - val_acc: 0.9754
Epoch 5/20
60000/60000 [==============================] - 4s 59us/step - loss: 0.1161 - acc: 0.9648 -
val_loss: 0.0798 - val_acc: 0.9763
Epoch 6/20
60000/60000 [==============================] - 4s 59us/step - loss: 0.1044 - acc: 0.9688 -
val_loss: 0.0734 - val_acc: 0.9768
Epoch 7/20
60000/60000 [==============================] - 3s 58us/step - loss: 0.0943 - acc: 0.9708 -
val_loss: 0.0693 - val_acc: 0.9788
Epoch 8/20
60000/60000 [==============================] - 4s 59us/step - loss: 0.0892 - acc: 0.9726 -
val_loss: 0.0710 - val_acc: 0.9792
Epoch 9/20
60000/60000 [==============================] - 4s 59us/step - loss: 0.0841 - acc: 0.9743 -
val_loss: 0.0687 - val_acc: 0.9799
Epoch 10/20
60000/60000 [==============================] - 4s 59us/step - loss: 0.0752 - acc: 0.9765 -
val_loss: 0.0643 - val_acc: 0.9809
Epoch 11/20
60000/60000 [==============================] - 4s 59us/step - loss: 0.0744 - acc: 0.9770 -
val_loss: 0.0600 - val_acc: 0.9811
Epoch 12/20
```

```
60000/60000 [==============================] - 4s 59us/step - loss: 0.0699 - acc: 0.9785 -
val_loss: 0.0600 - val_acc: 0.9829
Epoch 13/20
60000/60000 [==============================] - 4s 59us/step - loss: 0.0688 - acc: 0.9787 -
val_loss: 0.0625 - val_acc: 0.9820
Epoch 14/20
60000/60000 [==============================] - 4s 58us/step - loss: 0.0645 - acc: 0.9797 -
val_loss: 0.0588 - val_acc: 0.9835
Epoch 15/20
60000/60000 [==============================] - 4s 59us/step - loss: 0.0595 - acc: 0.9810 -
val_loss: 0.0643 - val_acc: 0.9827
Epoch 16/20
60000/60000 [==============================] - 4s 59us/step - loss: 0.0589 - acc: 0.9814 -
val_loss: 0.0621 - val_acc: 0.9834
Epoch 17/20
60000/60000 [==============================] - 4s 59us/step - loss: 0.0599 - acc: 0.9813 -
val_loss: 0.0652 - val_acc: 0.9823
Epoch 18/20
60000/60000 [==============================] - 4s 60us/step - loss: 0.0564 - acc: 0.9817 -
val_loss: 0.0635 - val_acc: 0.9824
Epoch 19/20
60000/60000 [==============================] - 4s 59us/step - loss: 0.0552 - acc: 0.9826 -
val_loss: 0.0623 - val_acc: 0.9828
Epoch 20/20
60000/60000 [==============================] - 4s 59us/step - loss: 0.0536 - acc: 0.9831 -
val_loss: 0.0619 - val_acc: 0.9831
```

In [100]:

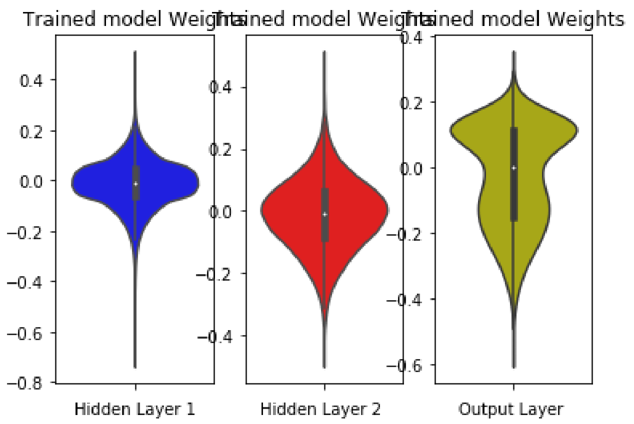
```
score = model_relu.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

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

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

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

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

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

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

```
Test score: 0.06188290925989168
Test accuracy: 0.9831
```



In [101]:

```
w_after = model_relu.get_weights()

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


fig = plt.figure()
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 activation + ADAM + Batch Normalization + Dropout with 2 hidden layers

In [102]:

```
# Multilayer perceptron
model_relu = Sequential()
model_relu.add(Dense(392, activation='relu', input_shape=(input_dim,)))
model_relu.add(BatchNormalization())
model_relu.add(Dropout(0.5))
model_relu.add(Dense(196, activation='relu'))
model_relu.add(BatchNormalization())
model_relu.add(Dropout(0.5))
model_relu.add(Dense(output_dim, activation='softmax'))

model_relu.summary()
```

```
Model: "sequential_24"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_92 (Dense)             (None, 392)               307720
_________________________________________________________________
batch_normalization_34 (Batc (None, 392)               1568
_________________________________________________________________
dropout_29 (Dropout)         (None, 392)               0
_________________________________________________________________
dense_93 (Dense)             (None, 196)               77028
```

```
_________________________________________________________________
batch_normalization_35 (Batc (None, 196)               784       
_________________________________________________________________
dropout_30 (Dropout)         (None, 196)               0         
_________________________________________________________________
dense_94 (Dense)             (None, 10)                1970      
=================================================================
Total params: 389,070
Trainable params: 387,894
Non-trainable params: 1,176
_________________________________________________________________
```

In [103]:

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

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

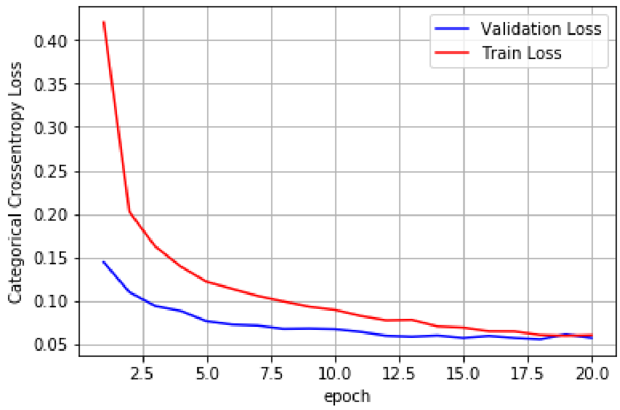
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 9s 152us/step - loss: 0.4204 - acc: 0.8732 - 
val_loss: 0.1443 - val_acc: 0.9536
Epoch 2/20
60000/60000 [==============================] - 5s 89us/step - loss: 0.2023 - acc: 0.9399 - 
val_loss: 0.1098 - val_acc: 0.9676
Epoch 3/20
60000/60000 [==============================] - 5s 90us/step - loss: 0.1625 - acc: 0.9502 - 
val_loss: 0.0939 - val_acc: 0.9713
Epoch 4/20
60000/60000 [==============================] - 5s 90us/step - loss: 0.1393 - acc: 0.9569 - 
val_loss: 0.0881 - val_acc: 0.9740
Epoch 5/20
60000/60000 [==============================] - 5s 90us/step - loss: 0.1219 - acc: 0.9622 - 
val_loss: 0.0764 - val_acc: 0.9758
Epoch 6/20
60000/60000 [==============================] - 5s 91us/step - loss: 0.1136 - acc: 0.9644 - 
val_loss: 0.0725 - val_acc: 0.9768
Epoch 7/20
60000/60000 [==============================] - 5s 90us/step - loss: 0.1054 - acc: 0.9673 - 
val_loss: 0.0713 - val_acc: 0.9788
Epoch 8/20
60000/60000 [==============================] - 5s 89us/step - loss: 0.0991 - acc: 0.9688 - 
val_loss: 0.0674 - val_acc: 0.9794
Epoch 9/20
60000/60000 [==============================] - 5s 90us/step - loss: 0.0930 - acc: 0.9703 - 
val_loss: 0.0678 - val_acc: 0.9802
Epoch 10/20
60000/60000 [==============================] - 5s 91us/step - loss: 0.0894 - acc: 0.9717 - 
val_loss: 0.0672 - val_acc: 0.9802
Epoch 11/20
60000/60000 [==============================] - 5s 91us/step - loss: 0.0825 - acc: 0.9745 - 
val_loss: 0.0641 - val_acc: 0.9809
Epoch 12/20
60000/60000 [==============================] - 5s 89us/step - loss: 0.0773 - acc: 0.9759 - 
val_loss: 0.0595 - val_acc: 0.9811
Epoch 13/20
60000/60000 [==============================] - 5s 91us/step - loss: 0.0779 - acc: 0.9750 - 
val_loss: 0.0584 - val_acc: 0.9814
Epoch 14/20
60000/60000 [==============================] - 6s 93us/step - loss: 0.0703 - acc: 0.9773 - 
val_loss: 0.0598 - val_acc: 0.9822
Epoch 15/20
60000/60000 [==============================] - 6s 92us/step - loss: 0.0690 - acc: 0.9781 - 
val_loss: 0.0569 - val_acc: 0.9842
Epoch 16/20
60000/60000 [==============================] - 5s 90us/step - loss: 0.0647 - acc: 0.9792 - 
val_loss: 0.0593 - val_acc: 0.9813
Epoch 17/20
60000/60000 [==============================] - 5s 90us/step - loss: 0.0646 - acc: 0.9799 - 
val_loss: 0.0569 - val_acc: 0.9831
Epoch 18/20
60000/60000 [==============================] - 5s 90us/step - loss: 0.0604 - acc: 0.9805 - 
val_loss: 0.0553 - val_acc: 0.9841
Epoch 19/20
60000/60000 [==============================] - 5s 91us/step - loss: 0.0595 - acc: 0.9807 - 
```

```
val_loss: 0.0612 - val_acc: 0.9818
Epoch 20/20
60000/60000 [==============================] - 6s 93us/step - loss: 0.0602 - acc: 0.9805 -
val_loss: 0.0569 - val_acc: 0.9829
```

In [104]:

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

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

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

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

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

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

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

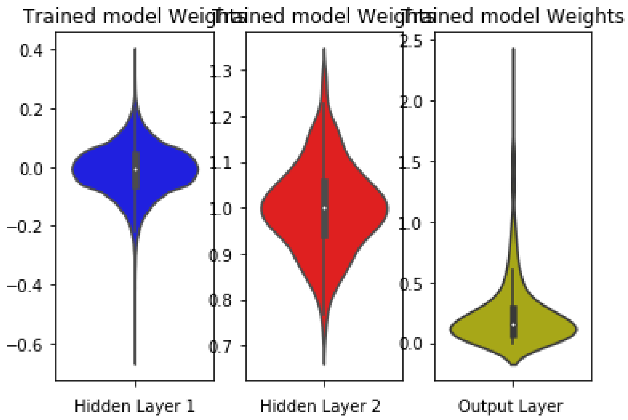
```
Test score: 0.05690854531452642
Test accuracy: 0.9829
```



In [105]:

```
w_after = model_relu.get_weights()

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


fig = plt.figure()
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 activation + ADAM with 3 hidden layers

In [106]:

```
# Multilayer perceptron

model = Sequential()
model.add(Dense(516, activation='relu', input_shape=(input_dim,)))
model.add(Dense(258, activation='relu'))
model.add(Dense(50, activation='relu'))
model.add(Dense(output_dim, activation='softmax'))

model.summary()
```

```
Model: "sequential_25"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_95 (Dense)             (None, 516)               405060    
_________________________________________________________________
dense_96 (Dense)             (None, 258)               133386    
_________________________________________________________________
dense_97 (Dense)             (None, 50)                12950     
_________________________________________________________________
dense_98 (Dense)             (None, 10)                510       
=================================================================
Total params: 551,906
Trainable params: 551,906
Non-trainable params: 0
_________________________________________________________________
```

In [107]:

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

history = model.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 [==============================] - 7s 120us/step - loss: 0.2391 - acc: 0.9292 - 
val_loss: 0.1139 - val_acc: 0.9644
Epoch 2/20
60000/60000 [==============================] - 4s 62us/step - loss: 0.0856 - acc: 0.9735 - 
val_loss: 0.0925 - val_acc: 0.9718
Epoch 3/20
60000/60000 [==============================] - 4s 63us/step - loss: 0.0548 - acc: 0.9827 - 
val_loss: 0.0658 - val_acc: 0.9782
```

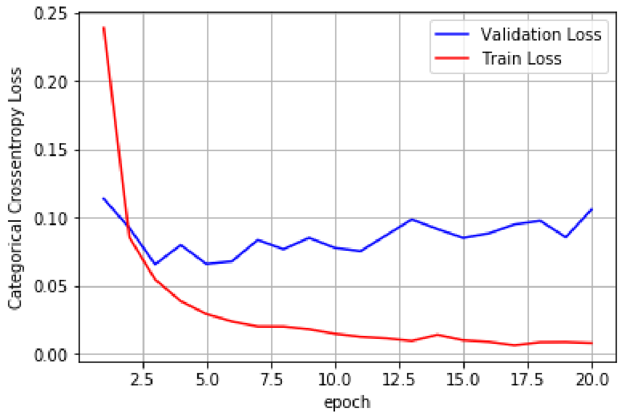
```
Epoch 4/20
60000/60000 [==============================] - 4s 63us/step - loss: 0.0388 - acc: 0.9871 -
val_loss: 0.0800 - val_acc: 0.9747
Epoch 5/20
60000/60000 [==============================] - 4s 63us/step - loss: 0.0295 - acc: 0.9904 -
val_loss: 0.0662 - val_acc: 0.9792
Epoch 6/20
60000/60000 [==============================] - 4s 64us/step - loss: 0.0240 - acc: 0.9922 -
val_loss: 0.0681 - val_acc: 0.9798
Epoch 7/20
60000/60000 [==============================] - 4s 64us/step - loss: 0.0203 - acc: 0.9935 -
val_loss: 0.0837 - val_acc: 0.9773
Epoch 8/20
60000/60000 [==============================] - 4s 63us/step - loss: 0.0202 - acc: 0.9934 -
val_loss: 0.0769 - val_acc: 0.9787
Epoch 9/20
60000/60000 [==============================] - 4s 63us/step - loss: 0.0183 - acc: 0.9940 -
val_loss: 0.0853 - val_acc: 0.9787
Epoch 10/20
60000/60000 [==============================] - 4s 63us/step - loss: 0.0150 - acc: 0.9953 -
val_loss: 0.0779 - val_acc: 0.9806
Epoch 11/20
60000/60000 [==============================] - 4s 62us/step - loss: 0.0127 - acc: 0.9957 -
val_loss: 0.0754 - val_acc: 0.9812
Epoch 12/20
60000/60000 [==============================] - 4s 62us/step - loss: 0.0116 - acc: 0.9960 -
val_loss: 0.0871 - val_acc: 0.9800
Epoch 13/20
60000/60000 [==============================] - 4s 63us/step - loss: 0.0097 - acc: 0.9968 -
val_loss: 0.0988 - val_acc: 0.9773
Epoch 14/20
60000/60000 [==============================] - 4s 63us/step - loss: 0.0142 - acc: 0.9955 -
val_loss: 0.0917 - val_acc: 0.9796
Epoch 15/20
60000/60000 [==============================] - 4s 63us/step - loss: 0.0102 - acc: 0.9964 -
val_loss: 0.0852 - val_acc: 0.9813
Epoch 16/20
60000/60000 [==============================] - 4s 62us/step - loss: 0.0090 - acc: 0.9971 -
val_loss: 0.0885 - val_acc: 0.9819
Epoch 17/20
60000/60000 [==============================] - 4s 63us/step - loss: 0.0065 - acc: 0.9978 -
val_loss: 0.0951 - val_acc: 0.9803
Epoch 18/20
60000/60000 [==============================] - 4s 62us/step - loss: 0.0087 - acc: 0.9974 -
val_loss: 0.0978 - val_acc: 0.9802
Epoch 19/20
60000/60000 [==============================] - 4s 63us/step - loss: 0.0088 - acc: 0.9974 -
val_loss: 0.0857 - val_acc: 0.9831
Epoch 20/20
60000/60000 [==============================] - 4s 63us/step - loss: 0.0081 - acc: 0.9975 -
val_loss: 0.1060 - val_acc: 0.9781
```

In [108]:

```
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
```

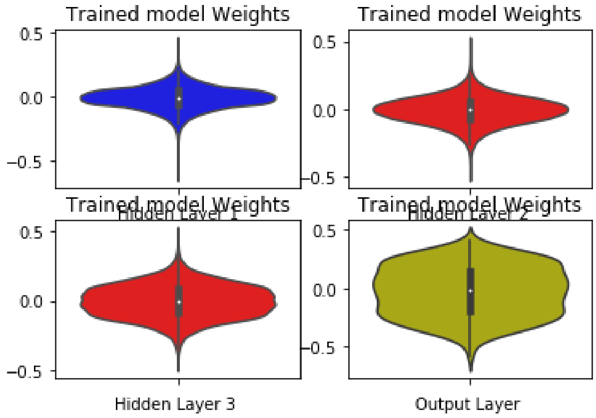
```
vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
```

```
Test score: 0.10599931993753521
Test accuracy: 0.9781
```



In [109]:

```
w_after = model.get_weights()

h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
h3_w = w_after[4].flatten().reshape(-1,1)
out_w = w_after[6].flatten().reshape(-1,1)


fig = plt.figure()
plt.title("Weight matrices after model trained")
plt.subplot(2, 2, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

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

plt.subplot(2, 2, 3)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h3_w, color='r')
plt.xlabel('Hidden Layer 3 ')

plt.subplot(2, 2, 4)
plt.title("Trained model Weights")
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output Layer ')
plt.show()
```



MLP + Relu activation + ADAM + Batch Normalization with 3 hidden layers

In [110]:

```
# Multilayer perceptron
model = Sequential()
model.add(Dense(516, activation='relu', input_shape=(input_dim,)))
model.add(BatchNormalization())
model.add(Dense(258, activation='relu'))
model.add(BatchNormalization())
model.add(Dense(50, activation='relu'))
model.add(BatchNormalization())
model.add(Dense(output_dim, activation='softmax'))

model.summary()
```

```
Model: "sequential_26"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_99 (Dense)             (None, 516)               405060    
_________________________________________________________________
batch_normalization_36 (Batc (None, 516)               2064      
_________________________________________________________________
dense_100 (Dense)            (None, 258)               133386    
_________________________________________________________________
batch_normalization_37 (Batc (None, 258)               1032      
_________________________________________________________________
dense_101 (Dense)            (None, 50)                12950     
_________________________________________________________________
batch_normalization_38 (Batc (None, 50)                200       
_________________________________________________________________
dense_102 (Dense)            (None, 10)                510       
=================================================================
Total params: 555,202
Trainable params: 553,554
Non-trainable params: 1,648
_________________________________________________________________
```

In [111]:

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

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

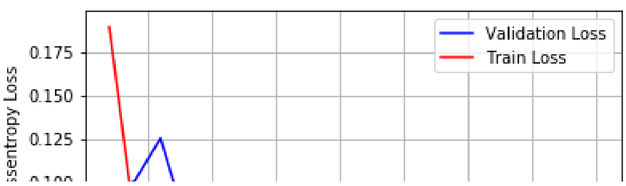
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 11s 182us/step - loss: 0.1897 - acc: 0.9451 - val_l
oss: 0.0929 - val_acc: 0.9716
Epoch 2/20
60000/60000 [==============================] - 7s 113us/step - loss: 0.0750 - acc: 0.9768 -
val_loss: 0.1012 - val_acc: 0.9685
Epoch 3/20
60000/60000 [==============================] - 7s 116us/step - loss: 0.0518 - acc: 0.9839 -
val_loss: 0.1256 - val_acc: 0.9605
Epoch 4/20
60000/60000 [==============================] - 7s 115us/step - loss: 0.0376 - acc: 0.9879 -
val_loss: 0.0757 - val_acc: 0.9767
Epoch 5/20
60000/60000 [==============================] - 7s 112us/step - loss: 0.0321 - acc: 0.9892 -
val_loss: 0.0847 - val_acc: 0.9744
Epoch 6/20
60000/60000 [==============================] - 7s 115us/step - loss: 0.0263 - acc: 0.9913 -
val_loss: 0.0889 - val_acc: 0.9744
Epoch 7/20
60000/60000 [==============================] - 7s 113us/step - loss: 0.0235 - acc: 0.9924 -
val_loss: 0.0721 - val_acc: 0.9783
Epoch 8/20
60000/60000 [==============================] - 7s 112us/step - loss: 0.0191 - acc: 0.9938 -
val_loss: 0.0800 - val_acc: 0.9768
Epoch 9/20
```

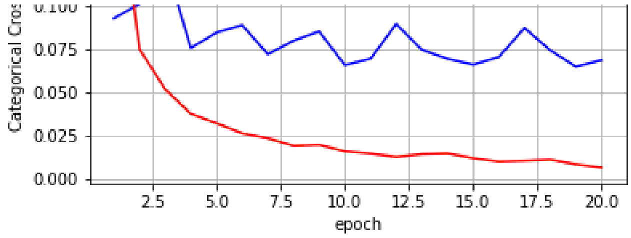
```
60000/60000 [==============================] - 7s 115us/step - loss: 0.0197 - acc: 0.9938 -
val_loss: 0.0853 - val_acc: 0.9757
Epoch 10/20
60000/60000 [==============================] - 7s 115us/step - loss: 0.0159 - acc: 0.9951 -
val_loss: 0.0658 - val_acc: 0.9814
Epoch 11/20
60000/60000 [==============================] - 7s 116us/step - loss: 0.0146 - acc: 0.9951 -
val_loss: 0.0695 - val_acc: 0.9819
Epoch 12/20
60000/60000 [==============================] - 7s 114us/step - loss: 0.0126 - acc: 0.9955 -
val_loss: 0.0896 - val_acc: 0.9773
Epoch 13/20
60000/60000 [==============================] - 7s 114us/step - loss: 0.0143 - acc: 0.9954 -
val_loss: 0.0747 - val_acc: 0.9802
Epoch 14/20
60000/60000 [==============================] - 7s 119us/step - loss: 0.0147 - acc: 0.9949 -
val_loss: 0.0695 - val_acc: 0.9818
Epoch 15/20
60000/60000 [==============================] - 7s 113us/step - loss: 0.0119 - acc: 0.9959 -
val_loss: 0.0661 - val_acc: 0.9816
Epoch 16/20
60000/60000 [==============================] - 7s 114us/step - loss: 0.0099 - acc: 0.9965 -
val_loss: 0.0705 - val_acc: 0.9818
Epoch 17/20
60000/60000 [==============================] - 7s 115us/step - loss: 0.0104 - acc: 0.9967 -
val_loss: 0.0873 - val_acc: 0.9785
Epoch 18/20
60000/60000 [==============================] - 7s 114us/step - loss: 0.0110 - acc: 0.9962 -
val_loss: 0.0744 - val_acc: 0.9811
Epoch 19/20
60000/60000 [==============================] - 7s 114us/step - loss: 0.0083 - acc: 0.9971 -
val_loss: 0.0649 - val_acc: 0.9832
Epoch 20/20
60000/60000 [==============================] - 7s 114us/step - loss: 0.0065 - acc: 0.9978 -
val_loss: 0.0687 - val_acc: 0.9834
```

In [112]:

```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)
```

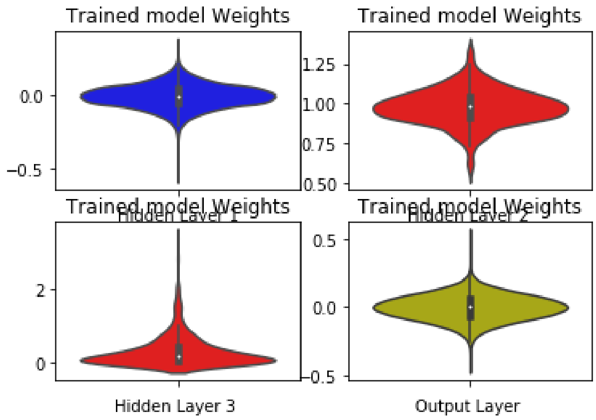
```
Test score: 0.06869542041149908
Test accuracy: 0.9834
```





In [113]:

```
w_after = model.get_weights()

h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
h3_w = w_after[4].flatten().reshape(-1,1)
out_w = w_after[6].flatten().reshape(-1,1)


fig = plt.figure()
plt.title("Weight matrices after model trained")
plt.subplot(2, 2, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

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

plt.subplot(2, 2, 3)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h3_w, color='r')
plt.xlabel('Hidden Layer 3 ')

plt.subplot(2, 2, 4)
plt.title("Trained model Weights")
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output Layer ')
plt.show()
```



MLP + Relu activation + ADAM + Dropout with 3 hidden layers

In [114]:

```
# Multilayer perceptron
from keras.layers import Dropout
model = Sequential()
model.add(Dense(516, activation='relu', input_shape=(input_dim,)))
model.add(Dropout(0.5))
model.add(Dense(258, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(50, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(output_dim, activation='softmax'))
```

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

model.summary()
```

```
Model: "sequential_27"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_103 (Dense)            (None, 516)               405060
_________________________________________________________________
dropout_31 (Dropout)         (None, 516)               0
_________________________________________________________________
dense_104 (Dense)            (None, 258)               133386
_________________________________________________________________
dropout_32 (Dropout)         (None, 258)               0
_________________________________________________________________
dense_105 (Dense)            (None, 50)                12950
_________________________________________________________________
dropout_33 (Dropout)         (None, 50)                0
_________________________________________________________________
dense_106 (Dense)            (None, 10)                510
=================================================================
Total params: 551,906
Trainable params: 551,906
Non-trainable params: 0
_________________________________________________________________
```

In [115]:

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

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

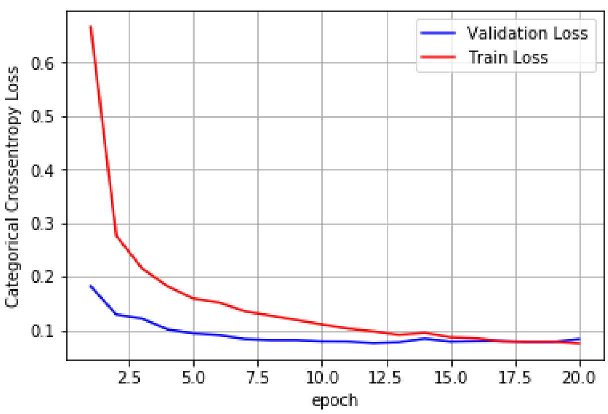
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 8s 133us/step - loss: 0.6660 - acc: 0.7910 -
val_loss: 0.1822 - val_acc: 0.9470
Epoch 2/20
60000/60000 [==============================] - 4s 69us/step - loss: 0.2760 - acc: 0.9281 -
val_loss: 0.1292 - val_acc: 0.9633
Epoch 3/20
60000/60000 [==============================] - 4s 68us/step - loss: 0.2154 - acc: 0.9452 -
val_loss: 0.1217 - val_acc: 0.9668
Epoch 4/20
60000/60000 [==============================] - 4s 68us/step - loss: 0.1818 - acc: 0.9538 -
val_loss: 0.1014 - val_acc: 0.9720
Epoch 5/20
60000/60000 [==============================] - 4s 67us/step - loss: 0.1591 - acc: 0.9598 -
val_loss: 0.0941 - val_acc: 0.9744
Epoch 6/20
60000/60000 [==============================] - 4s 69us/step - loss: 0.1517 - acc: 0.9611 -
val_loss: 0.0908 - val_acc: 0.9758
Epoch 7/20
60000/60000 [==============================] - 4s 68us/step - loss: 0.1353 - acc: 0.9656 -
val_loss: 0.0834 - val_acc: 0.9777
Epoch 8/20
60000/60000 [==============================] - 4s 68us/step - loss: 0.1271 - acc: 0.9673 -
val_loss: 0.0813 - val_acc: 0.9800
Epoch 9/20
60000/60000 [==============================] - 4s 71us/step - loss: 0.1192 - acc: 0.9695 -
val_loss: 0.0813 - val_acc: 0.9792
Epoch 10/20
60000/60000 [==============================] - 4s 71us/step - loss: 0.1106 - acc: 0.9707 -
val_loss: 0.0791 - val_acc: 0.9803
Epoch 11/20
60000/60000 [==============================] - 4s 68us/step - loss: 0.1032 - acc: 0.9729 -
val_loss: 0.0788 - val_acc: 0.9807
Epoch 12/20
60000/60000 [==============================] - 4s 68us/step - loss: 0.0978 - acc: 0.9745 -
val_loss: 0.0758 - val_acc: 0.9798
Epoch 13/20
60000/60000 [==============================] - 4s 67us/step - loss: 0.0912 - acc: 0.9758 -
val_loss: 0.0775 - val_acc: 0.9825
Epoch 14/20
```

```
60000/60000 [==============================] - 4s 68us/step - loss: 0.0951 - acc: 0.9749 -
val_loss: 0.0842 - val_acc: 0.9802
Epoch 15/20
60000/60000 [==============================] - 4s 67us/step - loss: 0.0867 - acc: 0.9770 -
val_loss: 0.0786 - val_acc: 0.9814
Epoch 16/20
60000/60000 [==============================] - 4s 68us/step - loss: 0.0849 - acc: 0.9773 -
val_loss: 0.0795 - val_acc: 0.9819
Epoch 17/20
60000/60000 [==============================] - 4s 68us/step - loss: 0.0789 - acc: 0.9792 -
val_loss: 0.0798 - val_acc: 0.9828
Epoch 18/20
60000/60000 [==============================] - 4s 68us/step - loss: 0.0780 - acc: 0.9789 -
val_loss: 0.0781 - val_acc: 0.9831
Epoch 19/20
60000/60000 [==============================] - 4s 68us/step - loss: 0.0784 - acc: 0.9790 -
val_loss: 0.0779 - val_acc: 0.9830
Epoch 20/20
60000/60000 [==============================] - 4s 68us/step - loss: 0.0751 - acc: 0.9799 -
val_loss: 0.0833 - val_acc: 0.9806
```

In [116]:

```
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)
```

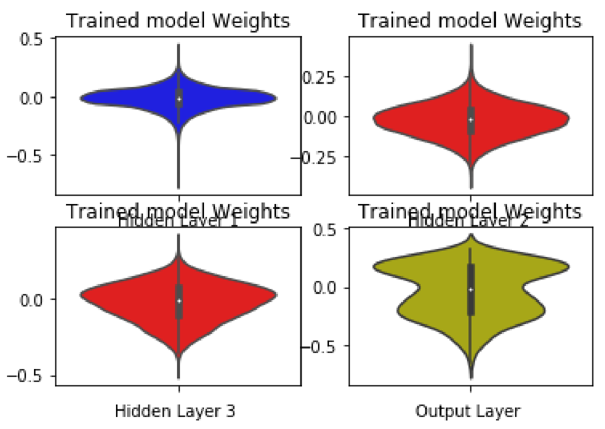
```
Test score: 0.08326539741690445
Test accuracy: 0.9806
```



In [117]:

```
w_after = model.get_weights()
```

```
h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
h3_w = w_after[4].flatten().reshape(-1,1)
out_w = w_after[6].flatten().reshape(-1,1)


fig = plt.figure()
plt.title("Weight matrices after model trained")
plt.subplot(2, 2, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

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

plt.subplot(2, 2, 3)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h3_w, color='r')
plt.xlabel('Hidden Layer 3 ')

plt.subplot(2, 2, 4)
plt.title("Trained model Weights")
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output Layer ')
plt.show()
```



MLP + Relu activation + ADAM + Batch Normalization + Dropout with 3 hidden layers

In [118]:

```
# Multilayer perceptron
model = Sequential()
model.add(Dense(516, activation='relu', input_shape=(input_dim,)))
model.add(BatchNormalization())
model.add(Dropout(0.5))
model.add(Dense(258, activation='relu'))
model.add(BatchNormalization())
model.add(Dropout(0.5))
model.add(Dense(50, activation='relu'))
model.add(BatchNormalization())
model.add(Dropout(0.5))
model.add(Dense(output_dim, activation='softmax'))

model.summary()
```

```
Model: "sequential_28"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_107 (Dense)            (None, 516)               405060    
_________________________________________________________________
batch_normalization_39 (Batc (None, 516)               2064      
_________________________________________________________________
dropout_34 (Dropout)         (None, 516)               0         
```

```
_________________________________________________________________
dense_108 (Dense)            (None, 258)               133386    
_________________________________________________________________
batch_normalization_40 (Batc (None, 258)               1032      
_________________________________________________________________
dropout_35 (Dropout)         (None, 258)               0         
_________________________________________________________________
dense_109 (Dense)            (None, 50)                12950     
_________________________________________________________________
batch_normalization_41 (Batc (None, 50)                200       
_________________________________________________________________
dropout_36 (Dropout)         (None, 50)                0         
_________________________________________________________________
dense_110 (Dense)            (None, 10)                510       
=================================================================
Total params: 555,202
Trainable params: 553,554
Non-trainable params: 1,648
_________________________________________________________________
```

In [119]:

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

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

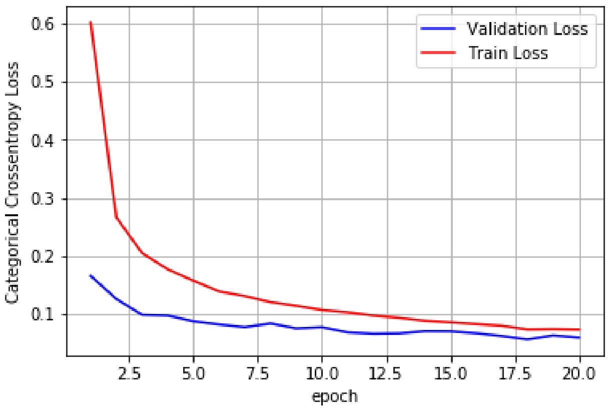
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 12s 197us/step - loss: 0.6016 - acc: 0.8208 - val_l
oss: 0.1655 - val_acc: 0.9496
Epoch 2/20
60000/60000 [==============================] - 7s 119us/step - loss: 0.2661 - acc: 0.9245 - 
val_loss: 0.1257 - val_acc: 0.9626
Epoch 3/20
60000/60000 [==============================] - 7s 119us/step - loss: 0.2046 - acc: 0.9420 - 
val_loss: 0.0984 - val_acc: 0.9698
Epoch 4/20
60000/60000 [==============================] - 7s 119us/step - loss: 0.1768 - acc: 0.9500 - 
val_loss: 0.0972 - val_acc: 0.9707
Epoch 5/20
60000/60000 [==============================] - 7s 120us/step - loss: 0.1571 - acc: 0.9556 - 
val_loss: 0.0872 - val_acc: 0.9749
Epoch 6/20
60000/60000 [==============================] - 7s 118us/step - loss: 0.1387 - acc: 0.9602 - 
val_loss: 0.0818 - val_acc: 0.9764
Epoch 7/20
60000/60000 [==============================] - 7s 120us/step - loss: 0.1307 - acc: 0.9643 - 
val_loss: 0.0770 - val_acc: 0.9777
Epoch 8/20
60000/60000 [==============================] - 7s 119us/step - loss: 0.1203 - acc: 0.9665 - 
val_loss: 0.0835 - val_acc: 0.9754
Epoch 9/20
60000/60000 [==============================] - 7s 118us/step - loss: 0.1139 - acc: 0.9678 - 
val_loss: 0.0750 - val_acc: 0.9794
Epoch 10/20
60000/60000 [==============================] - 7s 118us/step - loss: 0.1068 - acc: 0.9697 - 
val_loss: 0.0770 - val_acc: 0.9777
Epoch 11/20
60000/60000 [==============================] - 7s 118us/step - loss: 0.1027 - acc: 0.9711 - 
val_loss: 0.0682 - val_acc: 0.9813
Epoch 12/20
60000/60000 [==============================] - 7s 122us/step - loss: 0.0972 - acc: 0.9721 - 
val_loss: 0.0657 - val_acc: 0.9820
Epoch 13/20
60000/60000 [==============================] - 7s 125us/step - loss: 0.0932 - acc: 0.9741 - 
val_loss: 0.0663 - val_acc: 0.9816
Epoch 14/20
60000/60000 [==============================] - 7s 118us/step - loss: 0.0881 - acc: 0.9749 - 
val_loss: 0.0702 - val_acc: 0.9800
Epoch 15/20
60000/60000 [==============================] - 7s 121us/step - loss: 0.0854 - acc: 0.9759 - 
val_loss: 0.0700 - val_acc: 0.9813
Epoch 16/20
60000/60000 [==============================] - 7s 120us/step - loss: 0.0825 - acc: 0.9761 - 
```

```
val_loss: 0.0666 - val_acc: 0.9819
Epoch 17/20
60000/60000 [==============================] - 7s 118us/step - loss: 0.0795 - acc: 0.9774 -
val_loss: 0.0618 - val_acc: 0.9824
Epoch 18/20
60000/60000 [==============================] - 7s 121us/step - loss: 0.0732 - acc: 0.9786 -
val_loss: 0.0560 - val_acc: 0.9850
Epoch 19/20
60000/60000 [==============================] - 7s 121us/step - loss: 0.0737 - acc: 0.9780 -
val_loss: 0.0628 - val_acc: 0.9818
Epoch 20/20
60000/60000 [==============================] - 7s 120us/step - loss: 0.0730 - acc: 0.9781 -
val_loss: 0.0592 - val_acc: 0.9829
```

In [120]:

```
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)
```

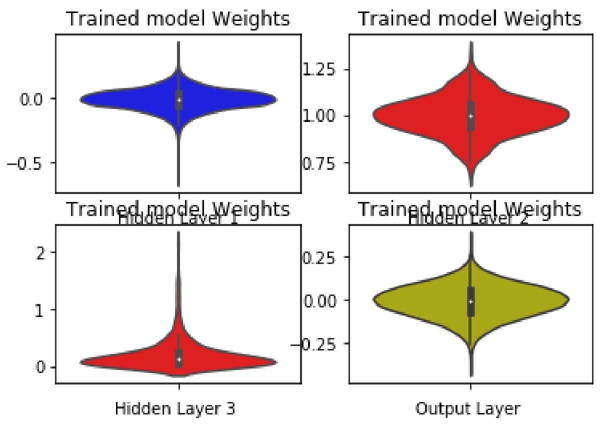
```
Test score: 0.059158047910808816
Test accuracy: 0.9829
```



In [121]:

```
w_after = model.get_weights()

h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
h3_w = w_after[4].flatten().reshape(-1,1)
out_w = w_after[6].flatten().reshape(-1,1)


fig = plt.figure()
```

```
plt.title("Weight matrices after model trained")
plt.subplot(2, 2, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

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

plt.subplot(2, 2, 3)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h3_w, color='r')
plt.xlabel('Hidden Layer 3 ')

plt.subplot(2, 2, 4)
plt.title("Trained model Weights")
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output Layer ')
plt.show()
```



MLP + Relu activation + ADAM with 5 hidden layers

In [122]:

```
# Multilayer perceptron

model2 = Sequential()
model2.add(Dense(645, activation='relu', input_shape=(input_dim,)))
model2.add(Dense(510, activation='relu'))
model2.add(Dense(387, activation='relu'))
model2.add(Dense(252, activation='relu'))
model2.add(Dense(129, activation='relu'))
model2.add(Dense(output_dim, activation='softmax'))

model2.summary()
```

```
Model: "sequential_29"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_111 (Dense)            (None, 645)               506325    
_________________________________________________________________
dense_112 (Dense)            (None, 510)               329460    
_________________________________________________________________
dense_113 (Dense)            (None, 387)               197757    
_________________________________________________________________
dense_114 (Dense)            (None, 252)               97776     
_________________________________________________________________
dense_115 (Dense)            (None, 129)               32637     
_________________________________________________________________
dense_116 (Dense)            (None, 10)                1300      
=================================================================
Total params: 1,165,255
Trainable params: 1,165,255
Non-trainable params: 0
```

____

In [123]:

```
model2.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history = model2.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, validatio
n_data=(X_test, Y_test))
```

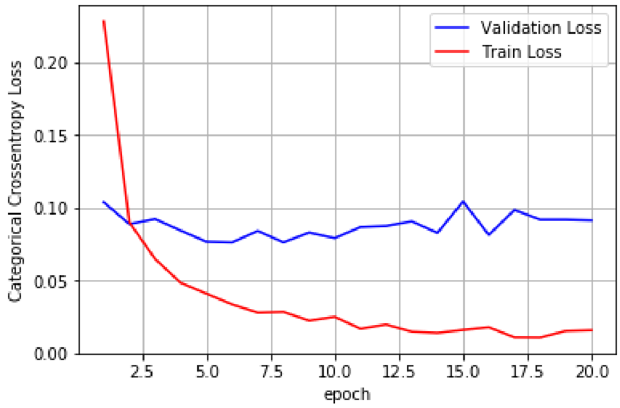
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 9s 156us/step - loss: 0.2283 - acc: 0.9299 -
val_loss: 0.1040 - val_acc: 0.9682
Epoch 2/20
60000/60000 [==============================] - 5s 84us/step - loss: 0.0901 - acc: 0.9723 -
val_loss: 0.0889 - val_acc: 0.9734
Epoch 3/20
60000/60000 [==============================] - 5s 83us/step - loss: 0.0650 - acc: 0.9804 -
val_loss: 0.0925 - val_acc: 0.9730
Epoch 4/20
60000/60000 [==============================] - 5s 83us/step - loss: 0.0486 - acc: 0.9850 -
val_loss: 0.0845 - val_acc: 0.9755
Epoch 5/20
60000/60000 [==============================] - 5s 84us/step - loss: 0.0412 - acc: 0.9877 -
val_loss: 0.0768 - val_acc: 0.9798
Epoch 6/20
60000/60000 [==============================] - 5s 84us/step - loss: 0.0338 - acc: 0.9894 -
val_loss: 0.0764 - val_acc: 0.9788
Epoch 7/20
60000/60000 [==============================] - 5s 84us/step - loss: 0.0281 - acc: 0.9915 -
val_loss: 0.0843 - val_acc: 0.9802
Epoch 8/20
60000/60000 [==============================] - 5s 84us/step - loss: 0.0286 - acc: 0.9916 -
val_loss: 0.0764 - val_acc: 0.9800
Epoch 9/20
60000/60000 [==============================] - 5s 82us/step - loss: 0.0226 - acc: 0.9937 -
val_loss: 0.0831 - val_acc: 0.9791
Epoch 10/20
60000/60000 [==============================] - 5s 83us/step - loss: 0.0252 - acc: 0.9927 -
val_loss: 0.0793 - val_acc: 0.9817
Epoch 11/20
60000/60000 [==============================] - 5s 83us/step - loss: 0.0170 - acc: 0.9948 -
val_loss: 0.0869 - val_acc: 0.9811
Epoch 12/20
60000/60000 [==============================] - 5s 83us/step - loss: 0.0199 - acc: 0.9941 -
val_loss: 0.0877 - val_acc: 0.9815
Epoch 13/20
60000/60000 [==============================] - 5s 89us/step - loss: 0.0150 - acc: 0.9956 -
val_loss: 0.0908 - val_acc: 0.9818
Epoch 14/20
60000/60000 [==============================] - 5s 89us/step - loss: 0.0141 - acc: 0.9958 -
val_loss: 0.0829 - val_acc: 0.9832
Epoch 15/20
60000/60000 [==============================] - 5s 83us/step - loss: 0.0162 - acc: 0.9952 -
val_loss: 0.1045 - val_acc: 0.9793
Epoch 16/20
60000/60000 [==============================] - 5s 84us/step - loss: 0.0181 - acc: 0.9954 -
val_loss: 0.0815 - val_acc: 0.9821
Epoch 17/20
60000/60000 [==============================] - 5s 84us/step - loss: 0.0111 - acc: 0.9969 -
val_loss: 0.0987 - val_acc: 0.9810
Epoch 18/20
60000/60000 [==============================] - 5s 84us/step - loss: 0.0109 - acc: 0.9971 -
val_loss: 0.0920 - val_acc: 0.9825
Epoch 19/20
60000/60000 [==============================] - 5s 83us/step - loss: 0.0155 - acc: 0.9957 -
val_loss: 0.0920 - val_acc: 0.9808
Epoch 20/20
60000/60000 [==============================] - 5s 84us/step - loss: 0.0160 - acc: 0.9958 -
val_loss: 0.0916 - val_acc: 0.9831
```

In [124]:

```
score = model2.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)
```

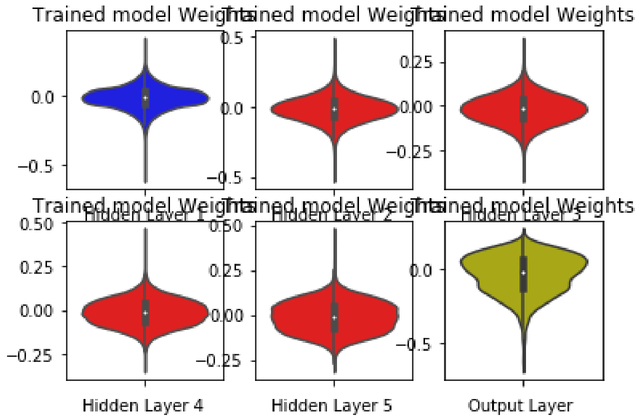
```
Test score: 0.09155124295547798
Test accuracy: 0.9831
```



In [125]:

```
w_after = model2.get_weights()

h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
h3_w = w_after[4].flatten().reshape(-1,1)
h4_w = w_after[6].flatten().reshape(-1,1)
h5_w = w_after[8].flatten().reshape(-1,1)
out_w = w_after[10].flatten().reshape(-1,1)


fig = plt.figure()
plt.title("Weight matrices after model trained")
plt.subplot(2, 3, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

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

plt.subplot(2, 3, 3)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h3_w, color='r')
plt.xlabel('Hidden Layer 3 ')

plt.subplot(2, 3, 4)
```

```
plt.subplot(2, 3, 4)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h4_w, color='r')
plt.xlabel('Hidden Layer 4 ')

plt.subplot(2, 3, 5)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h5_w, color='r')
plt.xlabel('Hidden Layer 5 ')

plt.subplot(2, 3, 6)
plt.title("Trained model Weights")
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output Layer ')
plt.show()
```



MLP + Relu activation + ADAM + Batch Normalization with 5 hidden layers

In [126]:

```
# Multilayer perceptron

model2 = Sequential()
model2.add(Dense(645, activation='relu', input_shape=(input_dim,)))
model.add(BatchNormalization())
model2.add(Dense(510, activation='relu'))
model.add(BatchNormalization())
model2.add(Dense(387, activation='relu'))
model.add(BatchNormalization())
model2.add(Dense(252, activation='relu'))
model.add(BatchNormalization())
model2.add(Dense(129, activation='relu'))
model.add(BatchNormalization())
model2.add(Dense(output_dim, activation='softmax'))

model2.summary()
```

```
Model: "sequential_30"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_117 (Dense)            (None, 645)               506325
_________________________________________________________________
dense_118 (Dense)            (None, 510)               329460
_________________________________________________________________
dense_119 (Dense)            (None, 387)               197757
_________________________________________________________________
dense_120 (Dense)            (None, 252)               97776
_________________________________________________________________
dense_121 (Dense)            (None, 129)               32637
_________________________________________________________________
dense_122 (Dense)            (None, 10)                1300
=================================================================
Total params: 1,165,255
Trainable params: 1,165,255
Non-trainable params: 0
_________________________________________________________________
```

In [127]:

```
model2.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history = model2.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, validatio
n_data=(X_test, Y_test))
```

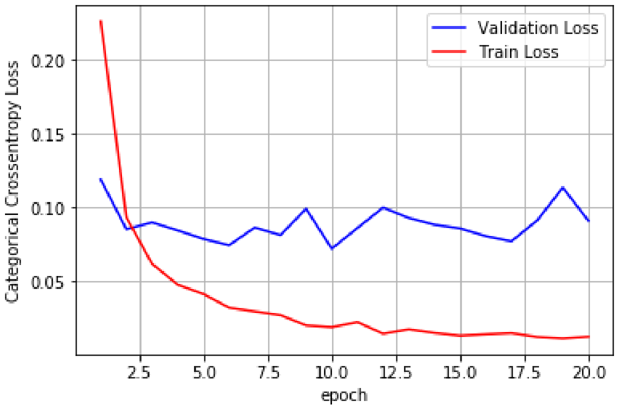
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 10s 161us/step - loss: 0.2261 - acc: 0.9313 - val_l
oss: 0.1190 - val_acc: 0.9636
Epoch 2/20
60000/60000 [==============================] - 5s 84us/step - loss: 0.0934 - acc: 0.9722 -
val_loss: 0.0854 - val_acc: 0.9738
Epoch 3/20
60000/60000 [==============================] - 5s 84us/step - loss: 0.0620 - acc: 0.9813 -
val_loss: 0.0900 - val_acc: 0.9750
Epoch 4/20
60000/60000 [==============================] - 5s 84us/step - loss: 0.0478 - acc: 0.9849 -
val_loss: 0.0846 - val_acc: 0.9777
Epoch 5/20
60000/60000 [==============================] - 5s 84us/step - loss: 0.0415 - acc: 0.9870 -
val_loss: 0.0788 - val_acc: 0.9783
Epoch 6/20
60000/60000 [==============================] - 5s 84us/step - loss: 0.0323 - acc: 0.9900 -
val_loss: 0.0745 - val_acc: 0.9801
Epoch 7/20
60000/60000 [==============================] - 5s 84us/step - loss: 0.0297 - acc: 0.9909 -
val_loss: 0.0865 - val_acc: 0.9784
Epoch 8/20
60000/60000 [==============================] - 5s 85us/step - loss: 0.0273 - acc: 0.9919 -
val_loss: 0.0814 - val_acc: 0.9788
Epoch 9/20
60000/60000 [==============================] - 5s 84us/step - loss: 0.0203 - acc: 0.9941 -
val_loss: 0.0993 - val_acc: 0.9797
Epoch 10/20
60000/60000 [==============================] - 5s 84us/step - loss: 0.0191 - acc: 0.9942 -
val_loss: 0.0722 - val_acc: 0.9824
Epoch 11/20
60000/60000 [==============================] - 5s 84us/step - loss: 0.0225 - acc: 0.9935 -
val_loss: 0.0863 - val_acc: 0.9791
Epoch 12/20
60000/60000 [==============================] - 5s 85us/step - loss: 0.0147 - acc: 0.9954 -
val_loss: 0.1001 - val_acc: 0.9784
Epoch 13/20
60000/60000 [==============================] - 5s 84us/step - loss: 0.0176 - acc: 0.9952 -
val_loss: 0.0930 - val_acc: 0.9802
Epoch 14/20
60000/60000 [==============================] - 5s 84us/step - loss: 0.0152 - acc: 0.9958 -
val_loss: 0.0885 - val_acc: 0.9812
Epoch 15/20
60000/60000 [==============================] - 5s 84us/step - loss: 0.0134 - acc: 0.9960 -
val_loss: 0.0859 - val_acc: 0.9820
Epoch 16/20
60000/60000 [==============================] - 5s 84us/step - loss: 0.0143 - acc: 0.9958 -
val_loss: 0.0807 - val_acc: 0.9826
Epoch 17/20
60000/60000 [==============================] - 5s 85us/step - loss: 0.0151 - acc: 0.9957 -
val_loss: 0.0772 - val_acc: 0.9835
Epoch 18/20
60000/60000 [==============================] - 5s 83us/step - loss: 0.0125 - acc: 0.9966 -
val_loss: 0.0913 - val_acc: 0.9832
Epoch 19/20
60000/60000 [==============================] - 5s 84us/step - loss: 0.0115 - acc: 0.9968 -
val_loss: 0.1136 - val_acc: 0.9807
Epoch 20/20
60000/60000 [==============================] - 5s 84us/step - loss: 0.0126 - acc: 0.9966 -
val_loss: 0.0911 - val_acc: 0.9830
```

In [128]:

```
score = model2.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])
```

```
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)
```

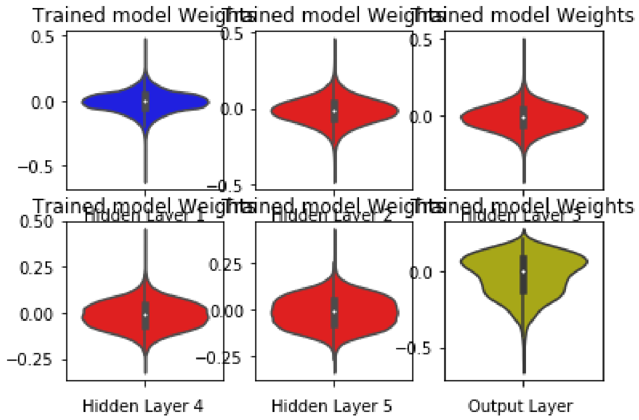
```
Test score: 0.09110382709081515
Test accuracy: 0.983
```



In [129]:

```
w_after = model2.get_weights()

h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
h3_w = w_after[4].flatten().reshape(-1,1)
h4_w = w_after[6].flatten().reshape(-1,1)
h5_w = w_after[8].flatten().reshape(-1,1)
out_w = w_after[10].flatten().reshape(-1,1)


fig = plt.figure()
plt.title("Weight matrices after model trained")
plt.subplot(2, 3, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

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

plt.subplot(2, 3, 3)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h3_w, color='r')
plt.xlabel('Hidden Layer 3 ')

plt.subplot(2, 3, 4)
plt.title("Trained model Weights")
```

```
plt.title("Trained model Weights")
ax = sns.violinplot(y=h4_w, color='r')
plt.xlabel('Hidden Layer 4 ')

plt.subplot(2, 3, 5)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h5_w, color='r')
plt.xlabel('Hidden Layer 5 ')

plt.subplot(2, 3, 6)
plt.title("Trained model Weights")
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output Layer ')
plt.show()
```



MLP + Relu activation + ADAM + Dropout with 5 hidden layers

In [130]:

```
# Multilayer perceptron

model2 = Sequential()
model2.add(Dense(645, activation='relu', input_shape=(input_dim,)))
model2.add(Dropout(0.5))
model2.add(Dense(510, activation='relu'))
model2.add(Dropout(0.5))
model2.add(Dense(387, activation='relu'))
model2.add(Dropout(0.5))
model2.add(Dense(252, activation='relu'))
model2.add(Dropout(0.5))
model2.add(Dense(129, activation='relu'))
model2.add(Dropout(0.5))
model2.add(Dense(output_dim, activation='softmax'))

model2.summary()
```

```
Model: "sequential_31"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_123 (Dense)            (None, 645)               506325
_________________________________________________________________
dropout_37 (Dropout)         (None, 645)               0
_________________________________________________________________
dense_124 (Dense)            (None, 510)               329460
_________________________________________________________________
dropout_38 (Dropout)         (None, 510)               0
_________________________________________________________________
dense_125 (Dense)            (None, 387)               197757
_________________________________________________________________
dropout_39 (Dropout)         (None, 387)               0
_________________________________________________________________
dense_126 (Dense)            (None, 252)               97776
_________________________________________________________________
dropout_40 (Dropout)         (None, 252)               0
_________________________________________________________________
dense_127 (Dense)            (None, 129)               32637
```

```
_________________________________________________________________
dropout_41 (Dropout)         (None, 129)               0
_________________________________________________________________
dense_128 (Dense)            (None, 10)                1300
=================================================================
Total params: 1,165,255
Trainable params: 1,165,255
Non-trainable params: 0
_________________________________________________________________
```

In [131]:

```
model2.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history = model2.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, validatio
n_data=(X_test, Y_test))
```

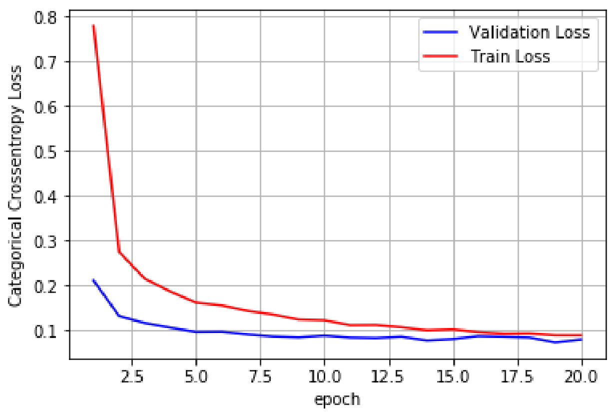
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 10s 169us/step - loss: 0.7789 - acc: 0.7449 - val_l
oss: 0.2111 - val_acc: 0.9400
Epoch 2/20
60000/60000 [==============================] - 5s 89us/step - loss: 0.2748 - acc: 0.9308 -
val_loss: 0.1316 - val_acc: 0.9643
Epoch 3/20
60000/60000 [==============================] - 5s 91us/step - loss: 0.2149 - acc: 0.9460 -
val_loss: 0.1159 - val_acc: 0.9700
Epoch 4/20
60000/60000 [==============================] - 5s 90us/step - loss: 0.1863 - acc: 0.9542 -
val_loss: 0.1058 - val_acc: 0.9734
Epoch 5/20
60000/60000 [==============================] - 5s 90us/step - loss: 0.1616 - acc: 0.9590 -
val_loss: 0.0959 - val_acc: 0.9740
Epoch 6/20
60000/60000 [==============================] - 5s 89us/step - loss: 0.1554 - acc: 0.9623 -
val_loss: 0.0964 - val_acc: 0.9754
Epoch 7/20
60000/60000 [==============================] - 5s 89us/step - loss: 0.1433 - acc: 0.9642 -
val_loss: 0.0905 - val_acc: 0.9761
Epoch 8/20
60000/60000 [==============================] - 5s 89us/step - loss: 0.1350 - acc: 0.9661 -
val_loss: 0.0860 - val_acc: 0.9781
Epoch 9/20
60000/60000 [==============================] - 5s 90us/step - loss: 0.1239 - acc: 0.9689 -
val_loss: 0.0839 - val_acc: 0.9795
Epoch 10/20
60000/60000 [==============================] - 5s 89us/step - loss: 0.1222 - acc: 0.9701 -
val_loss: 0.0880 - val_acc: 0.9788
Epoch 11/20
60000/60000 [==============================] - 5s 89us/step - loss: 0.1113 - acc: 0.9724 -
val_loss: 0.0834 - val_acc: 0.9790
Epoch 12/20
60000/60000 [==============================] - 5s 91us/step - loss: 0.1117 - acc: 0.9722 -
val_loss: 0.0823 - val_acc: 0.9804
Epoch 13/20
60000/60000 [==============================] - 5s 90us/step - loss: 0.1068 - acc: 0.9738 -
val_loss: 0.0854 - val_acc: 0.9814
Epoch 14/20
60000/60000 [==============================] - 5s 90us/step - loss: 0.0999 - acc: 0.9755 -
val_loss: 0.0770 - val_acc: 0.9820
Epoch 15/20
60000/60000 [==============================] - 5s 90us/step - loss: 0.1020 - acc: 0.9755 -
val_loss: 0.0801 - val_acc: 0.9818
Epoch 16/20
60000/60000 [==============================] - 5s 90us/step - loss: 0.0956 - acc: 0.9765 -
val_loss: 0.0867 - val_acc: 0.9800
Epoch 17/20
60000/60000 [==============================] - 5s 90us/step - loss: 0.0921 - acc: 0.9771 -
val_loss: 0.0854 - val_acc: 0.9803
Epoch 18/20
60000/60000 [==============================] - 5s 90us/step - loss: 0.0927 - acc: 0.9778 -
val_loss: 0.0835 - val_acc: 0.9818
Epoch 19/20
60000/60000 [==============================] - 5s 89us/step - loss: 0.0887 - acc: 0.9784 -
val_loss: 0.0726 - val_acc: 0.9827
Epoch 20/20
```

```
Epoch 20/20
60000/60000 [==============================] - 5s 90us/step - loss: 0.0886 - acc: 0.9788 - 
val_loss: 0.0790 - val_acc: 0.9830
```

In [132]:

```
score = model2.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)
```

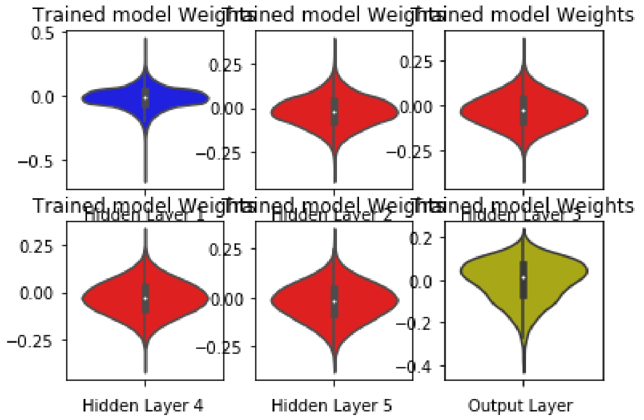
```
Test score: 0.0790262889877944
Test accuracy: 0.983
```



In [133]:

```
w_after = model2.get_weights()

h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
h3_w = w_after[4].flatten().reshape(-1,1)
h4_w = w_after[6].flatten().reshape(-1,1)
h5_w = w_after[8].flatten().reshape(-1,1)
out_w = w_after[10].flatten().reshape(-1,1)


fig = plt.figure()
plt.title("Weight matrices after model trained")
plt.subplot(2, 3, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

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

```
ax = sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden Layer 2 ')

plt.subplot(2, 3, 3)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h3_w, color='r')
plt.xlabel('Hidden Layer 3 ')

plt.subplot(2, 3, 4)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h4_w, color='r')
plt.xlabel('Hidden Layer 4 ')

plt.subplot(2, 3, 5)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h5_w, color='r')
plt.xlabel('Hidden Layer 5 ')

plt.subplot(2, 3, 6)
plt.title("Trained model Weights")
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output Layer ')
plt.show()
```



MLP + Relu activation + ADAM + Batch Normalization + Dropout with 5 hidden layers

In [134]:

```
# Multilayer perceptron
model2 = Sequential()
model2.add(Dense(645, activation='relu', input_shape=(input_dim,)))
model2.add(BatchNormalization())
model2.add(Dropout(0.5))
model2.add(Dense(510, activation='relu'))
model2.add(BatchNormalization())
model2.add(Dropout(0.5))
model2.add(Dense(387, activation='relu'))
model2.add(BatchNormalization())
model2.add(Dropout(0.5))
model2.add(Dense(252, activation='relu'))
model2.add(BatchNormalization())
model2.add(Dropout(0.5))
model2.add(Dense(129, activation='relu'))
model2.add(BatchNormalization())
model2.add(Dropout(0.5))
model2.add(Dense(output_dim, activation='softmax'))

model2.summary()
```

```
Model: "sequential_32"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_129 (Dense)            (None, 645)               506325
_________________________________________________________________
batch_normalization_47 (Batc (None, 645)               2580
_________________________________________________________________
```

```
dropout_42 (Dropout)         (None, 645)               0         
_________________________________________________________________
dense_130 (Dense)            (None, 510)               329460    
_________________________________________________________________
batch_normalization_48 (Batc (None, 510)               2040      
_________________________________________________________________
dropout_43 (Dropout)         (None, 510)               0         
_________________________________________________________________
dense_131 (Dense)            (None, 387)               197757    
_________________________________________________________________
batch_normalization_49 (Batc (None, 387)               1548      
_________________________________________________________________
dropout_44 (Dropout)         (None, 387)               0         
_________________________________________________________________
dense_132 (Dense)            (None, 252)               97776     
_________________________________________________________________
batch_normalization_50 (Batc (None, 252)               1008      
_________________________________________________________________
dropout_45 (Dropout)         (None, 252)               0         
_________________________________________________________________
dense_133 (Dense)            (None, 129)               32637     
_________________________________________________________________
batch_normalization_51 (Batc (None, 129)               516       
_________________________________________________________________
dropout_46 (Dropout)         (None, 129)               0         
_________________________________________________________________
dense_134 (Dense)            (None, 10)                1300      
=================================================================
Total params: 1,172,947
Trainable params: 1,169,101
Non-trainable params: 3,846
_________________________________________________________________
```

In [135]:

```
model2.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history = model2.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, validatio
n_data=(X_test, Y_test))
```

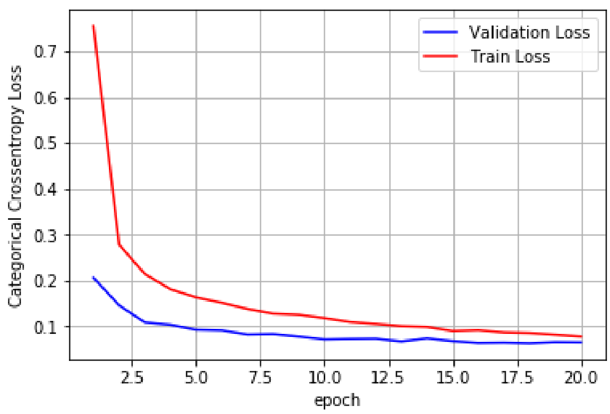
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 17s 282us/step - loss: 0.7552 - acc: 0.7723 - val_l
oss: 0.2059 - val_acc: 0.9419
Epoch 2/20
60000/60000 [==============================] - 11s 179us/step - loss: 0.2782 - acc: 0.9222 - val_l
oss: 0.1457 - val_acc: 0.9567
Epoch 3/20
60000/60000 [==============================] - 11s 181us/step - loss: 0.2141 - acc: 0.9400 - val_l
oss: 0.1085 - val_acc: 0.9701
Epoch 4/20
60000/60000 [==============================] - 11s 179us/step - loss: 0.1807 - acc: 0.9496 - val_l
oss: 0.1031 - val_acc: 0.9707
Epoch 5/20
60000/60000 [==============================] - 11s 181us/step - loss: 0.1630 - acc: 0.9545 - val_l
oss: 0.0924 - val_acc: 0.9741
Epoch 6/20
60000/60000 [==============================] - 11s 184us/step - loss: 0.1512 - acc: 0.9581 - val_l
oss: 0.0910 - val_acc: 0.9740
Epoch 7/20
60000/60000 [==============================] - 11s 184us/step - loss: 0.1378 - acc: 0.9611 - val_l
oss: 0.0820 - val_acc: 0.9771
Epoch 8/20
60000/60000 [==============================] - 11s 181us/step - loss: 0.1276 - acc: 0.9634 - val_l
oss: 0.0829 - val_acc: 0.9763
Epoch 9/20
60000/60000 [==============================] - 11s 180us/step - loss: 0.1252 - acc: 0.9647 - val_l
oss: 0.0776 - val_acc: 0.9778
Epoch 10/20
60000/60000 [==============================] - 11s 181us/step - loss: 0.1178 - acc: 0.9669 - val_l
oss: 0.0713 - val_acc: 0.9806
Epoch 11/20
60000/60000 [==============================] - 11s 180us/step - loss: 0.1093 - acc: 0.9693 - val_l
oss: 0.0723 - val_acc: 0.9792
Epoch 12/20
60000/60000 [==============================] - 11s 180us/step - loss: 0.1050 - acc: 0.9704 - val_l
```

```
oss: 0.0728 - val_acc: 0.9810
Epoch 13/20
60000/60000 [==============================] - 11s 179us/step - loss: 0.1001 - acc: 0.9720 - val_l
oss: 0.0667 - val_acc: 0.9813
Epoch 14/20
60000/60000 [==============================] - 11s 179us/step - loss: 0.0985 - acc: 0.9716 - val_l
oss: 0.0736 - val_acc: 0.9795
Epoch 15/20
60000/60000 [==============================] - 11s 180us/step - loss: 0.0896 - acc: 0.9747 - val_l
oss: 0.0674 - val_acc: 0.9817
Epoch 16/20
60000/60000 [==============================] - 11s 180us/step - loss: 0.0913 - acc: 0.9740 - val_l
oss: 0.0634 - val_acc: 0.9821
Epoch 17/20
60000/60000 [==============================] - 11s 180us/step - loss: 0.0865 - acc: 0.9764 - val_l
oss: 0.0641 - val_acc: 0.9821
Epoch 18/20
60000/60000 [==============================] - 11s 182us/step - loss: 0.0851 - acc: 0.9755 - val_l
oss: 0.0628 - val_acc: 0.9832
Epoch 19/20
60000/60000 [==============================] - 11s 182us/step - loss: 0.0815 - acc: 0.9766 - val_l
oss: 0.0652 - val_acc: 0.9816
Epoch 20/20
60000/60000 [==============================] - 11s 180us/step - loss: 0.0776 - acc: 0.9781 - val_l
oss: 0.0647 - val_acc: 0.9832
```

In [136]:

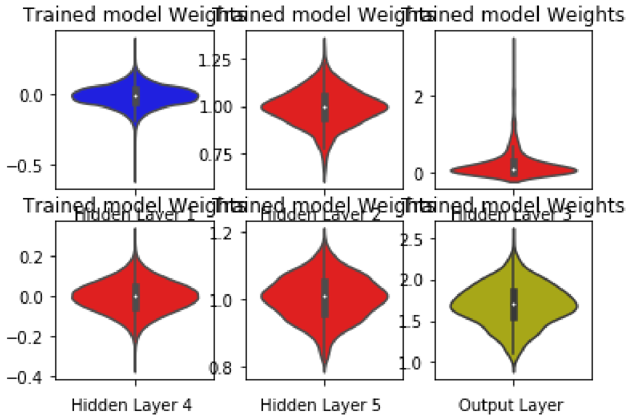
```python
score = model2.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

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: 0.06474938120327424
Test accuracy: 0.9832
```



In [137]:

```
w_after = model2.get_weights()

h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
h3_w = w_after[4].flatten().reshape(-1,1)
h4_w = w_after[6].flatten().reshape(-1,1)
h5_w = w_after[8].flatten().reshape(-1,1)
out_w = w_after[10].flatten().reshape(-1,1)


fig = plt.figure()
plt.title("Weight matrices after model trained")
plt.subplot(2, 3, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

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

plt.subplot(2, 3, 3)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h3_w, color='r')
plt.xlabel('Hidden Layer 3 ')

plt.subplot(2, 3, 4)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h4_w, color='r')
plt.xlabel('Hidden Layer 4 ')

plt.subplot(2, 3, 5)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h5_w, color='r')
plt.xlabel('Hidden Layer 5 ')

plt.subplot(2, 3, 6)
plt.title("Trained model Weights")
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output Layer ')
plt.show()
```



Observations

All tha below architecutres are implemented with fixing **relu** as **activation function** and **adam** as **optimization technique**.
We found that whatever might be the architecture, the model was overfitting when implemented with neither dropout nor batch normalization and with just batch normalization.
The model is converging fine when implemented either with just dropout or with both dropout and batch normalization.

In [3]:

```
from prettytable import PrettyTable
```

```
from prettytable import PrettyTable

x = PrettyTable()

x.field_names = ["Architecture", "NoOfNeurons/Layer", "BatchNormalization", "Dropouts", "Accuracy"]

x.add_row(["2 Hidden Layers","784-392-196-10","No","No","98.32%"])
x.add_row(["2 Hidden Layers","784-392-196-10","Yes","No","98.26%"])
x.add_row(["2 Hidden Layers","784-392-196-10","No","Yes","98.31%"])
x.add_row(["2 Hidden Layers","784-392-196-10","Yes","Yes","98.29%"])
x.add_row(["3 Hidden Layers","784-516-258-50-10","No","No","97.81%"])
x.add_row(["3 Hidden Layers","784-516-258-50-10","Yes","No","98.34%"])
x.add_row(["3 Hidden Layers","784-516-258-50-10","No","Yes","98.06%"])
x.add_row(["3 Hidden Layers","784-516-258-50-10","Yes","Yes","98.29%"])
x.add_row(["5 Hidden Layers","784-645-510-387-252-129-10","No","No","98.31%"])
x.add_row(["5 Hidden Layers","784-645-510-387-252-129-10","Yes","No","98.30%"])
x.add_row(["5 Hidden Layers","784-645-510-387-252-129-10","No","Yes","98.30%"])
x.add_row(["5 Hidden Layers","784-645-510-387-252-129-10","Yes","Yes","98.32%"])


print(x)
```

```
+-----------------+----------------------------+--------------------+----------+----------+
|   Architecture  |     NoOfNeurons/Layer      | BatchNormalization | Dropouts | Accuracy |
+-----------------+----------------------------+--------------------+----------+----------+
| 2 Hidden Layers |       784-392-196-10       |         No         |    No    |  98.32%  |
| 2 Hidden Layers |       784-392-196-10       |        Yes         |    No    |  98.26%  |
| 2 Hidden Layers |       784-392-196-10       |         No         |   Yes    |  98.31%  |
| 2 Hidden Layers |       784-392-196-10       |        Yes         |   Yes    |  98.29%  |
| 3 Hidden Layers |     784-516-258-50-10      |         No         |    No    |  97.81%  |
| 3 Hidden Layers |     784-516-258-50-10      |        Yes         |    No    |  98.34%  |
| 3 Hidden Layers |     784-516-258-50-10      |         No         |   Yes    |  98.06%  |
| 3 Hidden Layers |     784-516-258-50-10      |        Yes         |   Yes    |  98.29%  |
| 5 Hidden Layers | 784-645-510-387-252-129-10 |         No         |    No    |  98.31%  |
| 5 Hidden Layers | 784-645-510-387-252-129-10 |        Yes         |    No    |  98.30%  |
| 5 Hidden Layers | 784-645-510-387-252-129-10 |         No         |   Yes    |  98.30%  |
| 5 Hidden Layers | 784-645-510-387-252-129-10 |        Yes         |   Yes    |  98.32%  |
+-----------------+----------------------------+--------------------+----------+----------+
```