Keras -- MLPs on MNIST

1. Importing packages

In [1]:

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

```
Using TensorFlow backend.
```

2. Function for plotting Train and Test Error

In [0]:

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

3.Splitting data into train and test

In [3]:

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

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

In [4]:

```
X_train.shape
```

Out[4]:

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

In [5]:

```
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 [7]:

```
# 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 [8]:

```
# 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]
```

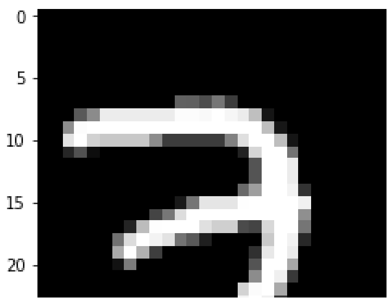
In [9]:

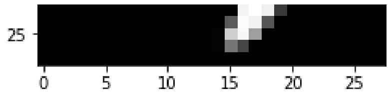
```
from tensorflow.examples.tutorials.mnist import input_data

mnist1 = input_data.read_data_sets("/tmp/data/", one_hot=True)
```

```
WARNING:tensorflow:From <ipython-input-9-f74fff8394f0>:3: read_data_sets (from
tensorflow.contrib.learn.python.learn.datasets.mnist) is deprecated and will be removed in a
future version.
Instructions for updating:
Please use alternatives such as official/mnist/dataset.py from tensorflow/models.
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/tensorflow/contrib/learn/python/learn/datasets/mnist.py:260: maybe_download (from
tensorflow.contrib.learn.python.learn.datasets.base) is deprecated and will be removed in a future
version.
Instructions for updating:
Please write your own downloading logic.
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/tensorflow/contrib/learn/python/learn/datasets/base.py:252: _internal_retry.
<locals>.wrap.<locals>.wrapped_fn (from tensorflow.contrib.learn.python.learn.datasets.base) is
deprecated and will be removed in a future version.
Instructions for updating:
Please use urllib or similar directly.
Successfully downloaded train-images-idx3-ubyte.gz 9912422 bytes.
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/tensorflow/contrib/learn/python/learn/datasets/mnist.py:262: extract_images (from
tensorflow.contrib.learn.python.learn.datasets.mnist) is deprecated and will be removed in a
future version.
Instructions for updating:
Please use tf.data to implement this functionality.
Extracting /tmp/data/train-images-idx3-ubyte.gz
Successfully downloaded train-labels-idx1-ubyte.gz 28881 bytes.
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/tensorflow/contrib/learn/python/learn/datasets/mnist.py:267: extract_labels (from
tensorflow.contrib.learn.python.learn.datasets.mnist) is deprecated and will be removed in a
future version.
Instructions for updating:
Please use tf.data to implement this functionality.
Extracting /tmp/data/train-labels-idx1-ubyte.gz
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/tensorflow/contrib/learn/python/learn/datasets/mnist.py:110: dense_to_one_hot (from
tensorflow.contrib.learn.python.learn.datasets.mnist) is deprecated and will be removed in a
future version.
Instructions for updating:
Please use tf.one_hot on tensors.
Successfully downloaded t10k-images-idx3-ubyte.gz 1648877 bytes.
Extracting /tmp/data/t10k-images-idx3-ubyte.gz
Successfully downloaded t10k-labels-idx1-ubyte.gz 4542 bytes.
Extracting /tmp/data/t10k-labels-idx1-ubyte.gz
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/tensorflow/contrib/learn/python/learn/datasets/mnist.py:290: DataSet.__init__ (from
tensorflow.contrib.learn.python.learn.datasets.mnist) is deprecated and will be removed in a
future version.
Instructions for updating:
Please use alternatives such as official/mnist/dataset.py from tensorflow/models.
```

In [10]:

```
%matplotlib inline
first_image = mnist1.train.images[0]
first_image = np.array(first_image, dtype='float')
pixels = first_image.reshape((28, 28))
plt.imshow(pixels, cmap='gray')
plt.show()
```





4. Normalizing data

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 [12]:

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

```
[0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.01176471 0.07058824 0.07058824 0.07058824
 0.49411765 0.53333333 0.68627451 0.10196078 0.65098039 1.
 0.96862745 0.49803922 0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.11764706 0.14117647 0.36862745 0.60392157
 0.66666667 0.99215686 0.99215686 0.99215686 0.99215686 0.99215686
 0.88235294 0.6745098  0.99215686 0.94901961 0.76470588 0.25098039
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.19215686
 0.93333333 0.99215686 0.99215686 0.99215686 0.99215686 0.99215686
 0.99215686 0.99215686 0.99215686 0.98431373 0.36470588 0.32156863
 0.32156863 0.21960784 0.15294118 0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.07058824 0.85882353 0.99215686
 0.99215686 0.99215686 0.99215686 0.99215686 0.77647059 0.71372549
 0.96862745 0.94509804 0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.31372549 0.61176471 0.41960784 0.99215686
 0.99215686 0.80392157 0.04313725 0.         0.16862745 0.60392157
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.05490196 0.00392157 0.60392157 0.99215686 0.35294118
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
```

```
0.         0.         0.         0.         0.         0.
0.         0.54509804 0.99215686 0.74509804 0.00784314 0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.04313725
0.74509804 0.99215686 0.2745098  0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.1372549  0.94509804
0.88235294 0.62745098 0.42352941 0.00392157 0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.31764706 0.94117647 0.99215686
0.99215686 0.46666667 0.09803922 0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.17647059 0.72941176 0.99215686 0.99215686
0.58823529 0.10588235 0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.0627451  0.36470588 0.98823529 0.99215686 0.73333333
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.97647059 0.99215686 0.97647059 0.25098039 0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.18039216 0.50980392 0.71764706 0.99215686
0.99215686 0.81176471 0.00784314 0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.15294118 0.58039216
0.89803922 0.99215686 0.99215686 0.99215686 0.98039216 0.71372549
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.09411765 0.44705882 0.86666667 0.99215686 0.99215686 0.99215686
0.99215686 0.78823529 0.30588235 0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.09019608 0.25882353 0.83529412 0.99215686
0.99215686 0.99215686 0.99215686 0.77647059 0.31764706 0.00784314
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.07058824 0.67058824
0.85882353 0.99215686 0.99215686 0.99215686 0.99215686 0.76470588
0.31372549 0.03529412 0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.21568627 0.6745098  0.88627451 0.99215686 0.99215686 0.99215686
0.99215686 0.95686275 0.52156863 0.04313725 0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.53333333 0.99215686
0.99215686 0.99215686 0.83137255 0.52941176 0.51764706 0.0627451
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
```

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

In [13]:

```
# 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'),
# ])

# 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 = 30
```

In [16]:

```
# start building a model
model = Sequential()

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

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

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

```
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/keras/backend/tensorflow_backend.py:66: The name tf.get_default_graph is deprecated. Plea
se use tf.compat.v1.get_default_graph instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/keras/backend/tensorflow_backend.py:541: The name tf.placeholder is deprecated. Please us
e tf.compat.v1.placeholder instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/keras/backend/tensorflow_backend.py:4432: The name tf.random_uniform is deprecated. Pleas
e use tf.random.uniform instead.
```

In [17]:

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

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


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

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

# that is why we converted out labels into vectors

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

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

# fit(self, x=None, y=None, batch_size=None, epochs=1, verbose=1, callbacks=None,
```

```
validation_split=0.0,
# validation_data=None, shuffle=True, class_weight=None, sample_weight=None, initial_epoch=0, step
s_per_epoch=None,
# validation_steps=None)

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

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

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

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

```
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/optimizers.py:793: The name t
f.train.Optimizer is deprecated. Please use tf.compat.v1.train.Optimizer instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/keras/backend/tensorflow_backend.py:3576: The name tf.log is deprecated. Please use tf.ma
th.log instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/tensorflow/python/ops/math_grad.py:1250: add_dispatch_support.<locals>.wrapper (from
tensorflow.python.ops.array_ops) is deprecated and will be removed in a future version.
Instructions for updating:
Use tf.where in 2.0, which has the same broadcast rule as np.where
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/keras/backend/tensorflow_backend.py:1033: The name tf.assign_add is deprecated. Please us
e tf.compat.v1.assign_add instead.

Train on 60000 samples, validate on 10000 samples
Epoch 1/30
60000/60000 [==============================] - 6s 107us/step - loss: 1.2656 - acc: 0.7131 -
val_loss: 0.8056 - val_acc: 0.8403
Epoch 2/30
60000/60000 [==============================] - 1s 24us/step - loss: 0.7086 - acc: 0.8460 -
val_loss: 0.6039 - val_acc: 0.8658
Epoch 3/30
60000/60000 [==============================] - 1s 24us/step - loss: 0.5824 - acc: 0.8627 -
val_loss: 0.5233 - val_acc: 0.8750
Epoch 4/30
60000/60000 [==============================] - 1s 25us/step - loss: 0.5222 - acc: 0.8709 -
val_loss: 0.4781 - val_acc: 0.8810
Epoch 5/30
60000/60000 [==============================] - 1s 24us/step - loss: 0.4853 - acc: 0.8760 -
val_loss: 0.4487 - val_acc: 0.8856
Epoch 6/30
60000/60000 [==============================] - 1s 24us/step - loss: 0.4600 - acc: 0.8803 -
val_loss: 0.4279 - val_acc: 0.8883
Epoch 7/30
60000/60000 [==============================] - 2s 25us/step - loss: 0.4412 - acc: 0.8840 -
val_loss: 0.4117 - val_acc: 0.8925
Epoch 8/30
60000/60000 [==============================] - 1s 24us/step - loss: 0.4265 - acc: 0.8868 -
val_loss: 0.3991 - val_acc: 0.8934
Epoch 9/30
60000/60000 [==============================] - 1s 24us/step - loss: 0.4146 - acc: 0.8893 -
val_loss: 0.3891 - val_acc: 0.8970
Epoch 10/30
60000/60000 [==============================] - 1s 24us/step - loss: 0.4048 - acc: 0.8916 -
val_loss: 0.3803 - val_acc: 0.8984
Epoch 11/30
60000/60000 [==============================] - 1s 24us/step - loss: 0.3964 - acc: 0.8931 -
val_loss: 0.3731 - val_acc: 0.8999
Epoch 12/30
60000/60000 [==============================] - 1s 24us/step - loss: 0.3892 - acc: 0.8943 -
val_loss: 0.3667 - val_acc: 0.9011
Epoch 13/30
60000/60000 [==============================] - 1s 24us/step - loss: 0.3829 - acc: 0.8959 -
val_loss: 0.3611 - val_acc: 0.9034
Epoch 14/30
60000/60000 [==============================] - 1s 24us/step - loss: 0.3773 - acc: 0.8971 -
val_loss: 0.3564 - val_acc: 0.9049
```

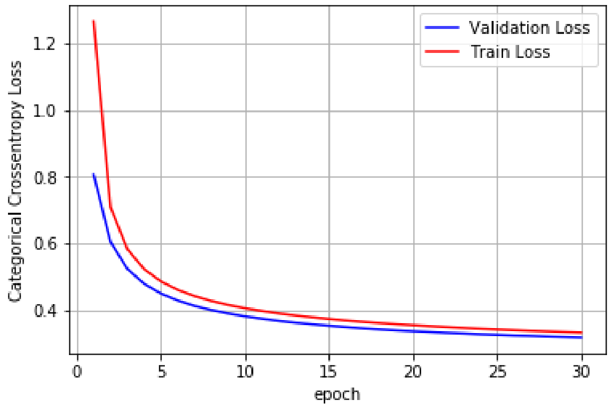
```
Epoch 15/30
60000/60000 [==============================] - 1s 25us/step - loss: 0.3723 - acc: 0.8982 -
val_loss: 0.3519 - val_acc: 0.9062
Epoch 16/30
60000/60000 [==============================] - 1s 24us/step - loss: 0.3678 - acc: 0.8996 -
val_loss: 0.3479 - val_acc: 0.9063
Epoch 17/30
60000/60000 [==============================] - 1s 24us/step - loss: 0.3638 - acc: 0.9000 -
val_loss: 0.3442 - val_acc: 0.9075
Epoch 18/30
60000/60000 [==============================] - 1s 24us/step - loss: 0.3601 - acc: 0.9010 -
val_loss: 0.3410 - val_acc: 0.9083
Epoch 19/30
60000/60000 [==============================] - 1s 24us/step - loss: 0.3567 - acc: 0.9015 -
val_loss: 0.3381 - val_acc: 0.9091
Epoch 20/30
60000/60000 [==============================] - 1s 25us/step - loss: 0.3536 - acc: 0.9025 -
val_loss: 0.3354 - val_acc: 0.9094
Epoch 21/30
60000/60000 [==============================] - 1s 24us/step - loss: 0.3506 - acc: 0.9031 -
val_loss: 0.3331 - val_acc: 0.9108
Epoch 22/30
60000/60000 [==============================] - 1s 24us/step - loss: 0.3479 - acc: 0.9034 -
val_loss: 0.3306 - val_acc: 0.9107
Epoch 23/30
60000/60000 [==============================] - 1s 24us/step - loss: 0.3454 - acc: 0.9042 -
val_loss: 0.3286 - val_acc: 0.9107
Epoch 24/30
60000/60000 [==============================] - 1s 25us/step - loss: 0.3431 - acc: 0.9047 -
val_loss: 0.3262 - val_acc: 0.9114
Epoch 25/30
60000/60000 [==============================] - 1s 24us/step - loss: 0.3409 - acc: 0.9054 -
val_loss: 0.3246 - val_acc: 0.9112
Epoch 26/30
60000/60000 [==============================] - 1s 24us/step - loss: 0.3388 - acc: 0.9060 -
val_loss: 0.3226 - val_acc: 0.9120
Epoch 27/30
60000/60000 [==============================] - 2s 25us/step - loss: 0.3368 - acc: 0.9063 -
val_loss: 0.3214 - val_acc: 0.9122
Epoch 28/30
60000/60000 [==============================] - 1s 24us/step - loss: 0.3350 - acc: 0.9066 -
val_loss: 0.3195 - val_acc: 0.9125
Epoch 29/30
60000/60000 [==============================] - 1s 24us/step - loss: 0.3332 - acc: 0.9072 -
val_loss: 0.3181 - val_acc: 0.9128
Epoch 30/30
60000/60000 [==============================] - 1s 25us/step - loss: 0.3315 - acc: 0.9077 -
val_loss: 0.3165 - val_acc: 0.9132
```

In [18]:

```
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: 0.3165304104745388
Test accuracy: 0.9132
```



In [19]:

```
score1 = model.evaluate(X_train, Y_train, verbose=0)
print('Train score:', score1[0])
print('Train accuracy:', score1[1])
```

```
Train score: 0.33035434688329696
Train accuracy: 0.90835
```

MLP + ReLU + ADAM

5. Two Hidden layers (input = 784,number of neurons in layer 1 = 512,number of neurons in layer 2 = 128,output = 10

1. Number of neurons here are activation functions.
2. Here activation function used is 'relu' and optimizer used is 'adam'.
3. Number of epochs is 40 and Batch_size is 128.
4. We used our metric as 'accuracy'.

In [20]:

```
import keras
epochs1 = 40
model_relu = Sequential()
model_relu.add(Dense(512, activation='relu', input_shape=(input_dim,), kernel_initializer=keras.ini
tializers.he_normal(seed=None)))
model_relu.add(Dense(128, activation='relu', kernel_initializer=keras.initializers.he_normal(seed=N
one)) )
model_relu.add(Dense(output_dim, activation='softmax'))

print(model_relu.summary())

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

history = model_relu.fit(X_train, Y_train, batch_size=batch_size, epochs=epochs1, verbose=1, valida
tion_data=(X_test, Y_test))
```

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_2 (Dense)              (None, 512)               401920    
_________________________________________________________________
dense_3 (Dense)              (None, 128)               65664     
_________________________________________________________________
```

```
dense_4 (Dense)              (None, 10)                1290
=================================================================
Total params: 468,874
Trainable params: 468,874
Non-trainable params: 0
_________________________________________________________________
None
Train on 60000 samples, validate on 10000 samples
Epoch 1/40
60000/60000 [==============================] - 2s 39us/step - loss: 0.2316 - acc: 0.9317 -
val_loss: 0.1059 - val_acc: 0.9690
Epoch 2/40
60000/60000 [==============================] - 2s 33us/step - loss: 0.0862 - acc: 0.9740 -
val_loss: 0.0794 - val_acc: 0.9762
Epoch 3/40
60000/60000 [==============================] - 2s 36us/step - loss: 0.0530 - acc: 0.9840 -
val_loss: 0.0689 - val_acc: 0.9785
Epoch 4/40
60000/60000 [==============================] - 2s 34us/step - loss: 0.0374 - acc: 0.9883 -
val_loss: 0.0620 - val_acc: 0.9810
Epoch 5/40
60000/60000 [==============================] - 2s 33us/step - loss: 0.0260 - acc: 0.9919 -
val_loss: 0.0664 - val_acc: 0.9797
Epoch 6/40
60000/60000 [==============================] - 2s 34us/step - loss: 0.0208 - acc: 0.9934 -
val_loss: 0.0725 - val_acc: 0.9807
Epoch 7/40
60000/60000 [==============================] - 2s 33us/step - loss: 0.0186 - acc: 0.9938 -
val_loss: 0.0732 - val_acc: 0.9799
Epoch 8/40
60000/60000 [==============================] - 2s 34us/step - loss: 0.0154 - acc: 0.9947 -
val_loss: 0.0932 - val_acc: 0.9771
Epoch 9/40
60000/60000 [==============================] - 2s 34us/step - loss: 0.0121 - acc: 0.9961 -
val_loss: 0.0843 - val_acc: 0.9799
Epoch 10/40
60000/60000 [==============================] - 2s 35us/step - loss: 0.0094 - acc: 0.9970 -
val_loss: 0.0795 - val_acc: 0.9800
Epoch 11/40
60000/60000 [==============================] - 2s 34us/step - loss: 0.0100 - acc: 0.9970 -
val_loss: 0.0860 - val_acc: 0.9800
Epoch 12/40
60000/60000 [==============================] - 2s 33us/step - loss: 0.0136 - acc: 0.9950 -
val_loss: 0.0929 - val_acc: 0.9767
Epoch 13/40
60000/60000 [==============================] - 2s 33us/step - loss: 0.0093 - acc: 0.9968 -
val_loss: 0.0880 - val_acc: 0.9798
Epoch 14/40
60000/60000 [==============================] - 2s 34us/step - loss: 0.0087 - acc: 0.9972 -
val_loss: 0.0871 - val_acc: 0.9813
Epoch 15/40
60000/60000 [==============================] - 2s 32us/step - loss: 0.0082 - acc: 0.9974 -
val_loss: 0.0884 - val_acc: 0.9796
Epoch 16/40
60000/60000 [==============================] - 2s 33us/step - loss: 0.0076 - acc: 0.9975 -
val_loss: 0.0838 - val_acc: 0.9809
Epoch 17/40
60000/60000 [==============================] - 2s 34us/step - loss: 0.0077 - acc: 0.9977 -
val_loss: 0.0812 - val_acc: 0.9832
Epoch 18/40
60000/60000 [==============================] - 2s 34us/step - loss: 0.0078 - acc: 0.9974 -
val_loss: 0.0838 - val_acc: 0.9817
Epoch 19/40
60000/60000 [==============================] - 2s 34us/step - loss: 0.0079 - acc: 0.9975 -
val_loss: 0.0859 - val_acc: 0.9814
Epoch 20/40
60000/60000 [==============================] - 2s 34us/step - loss: 0.0083 - acc: 0.9973 -
val_loss: 0.0810 - val_acc: 0.9827
Epoch 21/40
60000/60000 [==============================] - 2s 33us/step - loss: 0.0068 - acc: 0.9981 -
val_loss: 0.0891 - val_acc: 0.9822
Epoch 22/40
60000/60000 [==============================] - 2s 33us/step - loss: 0.0058 - acc: 0.9980 -
val_loss: 0.0996 - val_acc: 0.9820
Epoch 23/40
60000/60000 [==============================] - 2s 33us/step - loss: 0.0069 - acc: 0.9978 -
val_loss: 0.0907 - val_acc: 0.9825
```

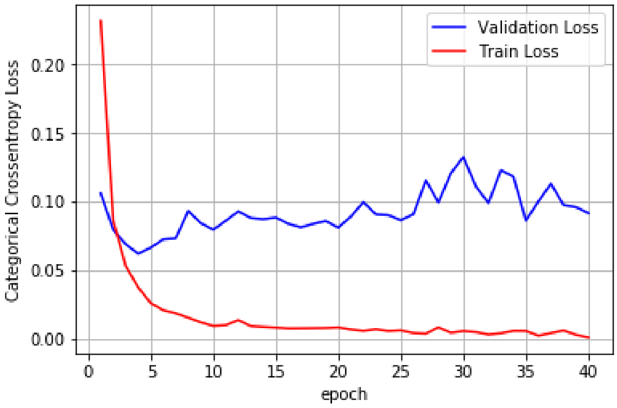
```
Epoch 24/40
60000/60000 [==============================] - 2s 33us/step - loss: 0.0057 - acc: 0.9983 -
val_loss: 0.0902 - val_acc: 0.9827
Epoch 25/40
60000/60000 [==============================] - 2s 34us/step - loss: 0.0062 - acc: 0.9981 -
val_loss: 0.0864 - val_acc: 0.9841
Epoch 26/40
60000/60000 [==============================] - 2s 33us/step - loss: 0.0042 - acc: 0.9989 -
val_loss: 0.0908 - val_acc: 0.9828
Epoch 27/40
60000/60000 [==============================] - 2s 32us/step - loss: 0.0037 - acc: 0.9989 -
val_loss: 0.1155 - val_acc: 0.9799
Epoch 28/40
60000/60000 [==============================] - 2s 32us/step - loss: 0.0083 - acc: 0.9974 -
val_loss: 0.0993 - val_acc: 0.9821
Epoch 29/40
60000/60000 [==============================] - 2s 35us/step - loss: 0.0044 - acc: 0.9986 -
val_loss: 0.1206 - val_acc: 0.9796
Epoch 30/40
60000/60000 [==============================] - 2s 34us/step - loss: 0.0057 - acc: 0.9983 -
val_loss: 0.1325 - val_acc: 0.9790
Epoch 31/40
60000/60000 [==============================] - 2s 33us/step - loss: 0.0049 - acc: 0.9985 -
val_loss: 0.1109 - val_acc: 0.9808
Epoch 32/40
60000/60000 [==============================] - 2s 33us/step - loss: 0.0031 - acc: 0.9989 -
val_loss: 0.0989 - val_acc: 0.9830
Epoch 33/40
60000/60000 [==============================] - 2s 34us/step - loss: 0.0041 - acc: 0.9988 -
val_loss: 0.1228 - val_acc: 0.9800
Epoch 34/40
60000/60000 [==============================] - 2s 33us/step - loss: 0.0058 - acc: 0.9983 -
val_loss: 0.1182 - val_acc: 0.9805
Epoch 35/40
60000/60000 [==============================] - 2s 33us/step - loss: 0.0057 - acc: 0.9984 -
val_loss: 0.0861 - val_acc: 0.9862
Epoch 36/40
60000/60000 [==============================] - 2s 33us/step - loss: 0.0023 - acc: 0.9994 -
val_loss: 0.1002 - val_acc: 0.9842
Epoch 37/40
60000/60000 [==============================] - 2s 33us/step - loss: 0.0042 - acc: 0.9988 -
val_loss: 0.1130 - val_acc: 0.9825
Epoch 38/40
60000/60000 [==============================] - 2s 33us/step - loss: 0.0060 - acc: 0.9983 -
val_loss: 0.0975 - val_acc: 0.9833
Epoch 39/40
60000/60000 [==============================] - 2s 33us/step - loss: 0.0030 - acc: 0.9991 -
val_loss: 0.0960 - val_acc: 0.9854
Epoch 40/40
60000/60000 [==============================] - 2s 33us/step - loss: 9.6561e-04 - acc: 0.9998 - val
_loss: 0.0916 - val_acc: 0.9857
```

In [21]:

```
score1 = model_relu.evaluate(X_train, Y_train, verbose=0)
print('Train score:', score1[0])
print('Train accuracy:', score1[1])
print("##############################################")
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,epochs1+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
```

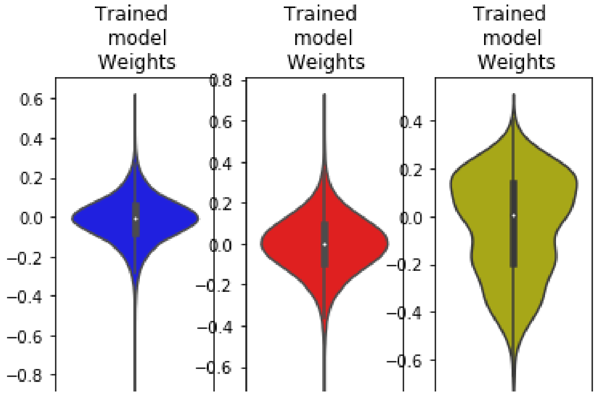
```
# loss : training loss
# acc : train accuracy
# for each key in histrory.histrory we will have a list of length equal to number of epochs


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

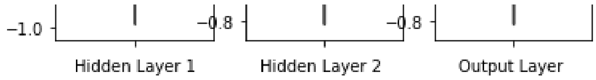
```
Train score: 0.0011970603236469894
Train accuracy: 0.9997
#############################################
Test score: 0.09155446254908205
Test accuracy: 0.9857
```



In [23]:

```
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 \n model\n Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

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

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





5. MLP + Dropout + AdamOptimizer

6. Two Hidden layers (input = 784,number of neurons in layer 1 = 512,number of neurons in layer 2 = 128,output = 10) with batch normalization and dropouts

1. Number of neurons here are activation functions.
2. Here activation function used is 'relu' and optimizer used is 'adam'.
3. Number of epochs is 20 and Batch_size is 128.
4. We used our metric as 'accuracy'.
5. We used Batch normalization and dropout at Layer1 and Layer2.
6. Dropout rate is 0.5

In [24]:

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

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


model_drop = Sequential()

model_drop.add(Dense(512, activation='relu', input_shape=(input_dim,), kernel_initializer=keras.initializers.he_uniform(seed=None)))
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

model_drop.add(Dense(128, activation='relu', kernel_initializer=keras.initializers.he_uniform(seed=None)) )
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

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


model_drop.summary()
```

```
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:3733: calling dropout (from tensorflow.python.ops.nn_ops) with keep_prob is deprecated and will be removed in a future version.
Instructions for updating:
Please use `rate` instead of `keep_prob`. Rate should be set to `rate = 1 - keep_prob`.
Model: "sequential_3"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_5 (Dense)              (None, 512)               401920
_________________________________________________________________
batch_normalization_1 (Batch (None, 512)               2048
_________________________________________________________________
dropout_1 (Dropout)          (None, 512)               0
_________________________________________________________________
dense_6 (Dense)              (None, 128)               65664
_________________________________________________________________
batch_normalization_2 (Batch (None, 128)               512
_________________________________________________________________
dropout_2 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_7 (Dense)              (None, 10)                1290
=================================================================
Total params: 471,434
Trainable params: 470,154
```

```
Non-trainable params: 1,280
_________________________________________________________________
```

In [25]:

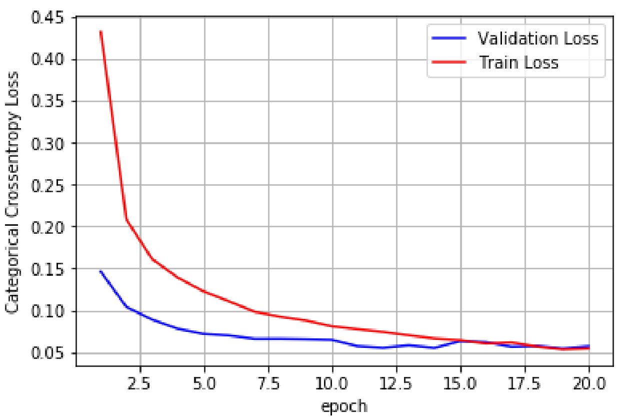
```
epoch2 = 20
model_drop.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=epoch2, verbose=1, validat
ion_data=(X_test, Y_test))
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 4s 66us/step - loss: 0.4317 - acc: 0.8690 -
val_loss: 0.1460 - val_acc: 0.9550
Epoch 2/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.2082 - acc: 0.9378 -
val_loss: 0.1039 - val_acc: 0.9673
Epoch 3/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.1610 - acc: 0.9519 -
val_loss: 0.0888 - val_acc: 0.9720
Epoch 4/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.1389 - acc: 0.9579 -
val_loss: 0.0779 - val_acc: 0.9747
Epoch 5/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.1226 - acc: 0.9623 -
val_loss: 0.0718 - val_acc: 0.9769
Epoch 6/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.1105 - acc: 0.9658 -
val_loss: 0.0699 - val_acc: 0.9783
Epoch 7/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.0981 - acc: 0.9695 -
val_loss: 0.0658 - val_acc: 0.9785
Epoch 8/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.0922 - acc: 0.9710 -
val_loss: 0.0659 - val_acc: 0.9784
Epoch 9/20
60000/60000 [==============================] - 3s 54us/step - loss: 0.0877 - acc: 0.9725 -
val_loss: 0.0654 - val_acc: 0.9803
Epoch 10/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.0809 - acc: 0.9753 -
val_loss: 0.0647 - val_acc: 0.9792
Epoch 11/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.0774 - acc: 0.9755 -
val_loss: 0.0571 - val_acc: 0.9807
Epoch 12/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.0741 - acc: 0.9766 -
val_loss: 0.0552 - val_acc: 0.9822
Epoch 13/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.0701 - acc: 0.9776 -
val_loss: 0.0582 - val_acc: 0.9817
Epoch 14/20
60000/60000 [==============================] - 3s 54us/step - loss: 0.0663 - acc: 0.9791 -
val_loss: 0.0550 - val_acc: 0.9827
Epoch 15/20
60000/60000 [==============================] - 3s 54us/step - loss: 0.0643 - acc: 0.9794 -
val_loss: 0.0631 - val_acc: 0.9809
Epoch 16/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.0602 - acc: 0.9806 -
val_loss: 0.0620 - val_acc: 0.9802
Epoch 17/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.0616 - acc: 0.9801 -
val_loss: 0.0564 - val_acc: 0.9827
Epoch 18/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.0566 - acc: 0.9824 -
val_loss: 0.0573 - val_acc: 0.9827
Epoch 19/20
60000/60000 [==============================] - 3s 54us/step - loss: 0.0533 - acc: 0.9829 -
val_loss: 0.0544 - val_acc: 0.9845
Epoch 20/20
60000/60000 [==============================] - 3s 54us/step - loss: 0.0543 - acc: 0.9821 -
val_loss: 0.0570 - val_acc: 0.9827
```

In [26]:

```
score1 = model_drop.evaluate(X_train, Y_train, verbose=0)
print('Train score:', score1[0])
print('Train accuracy:', score1[1])
print("###############################################")
score = model_drop.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

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

# list of epoch numbers
x = list(range(1,epoch2+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)
```

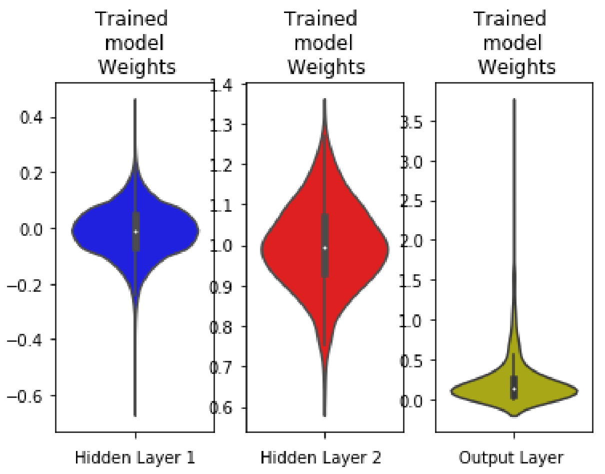
```
Train score: 0.011504149301705183
Train accuracy: 0.9963
###############################################
Test score: 0.056958603417154516
Test accuracy: 0.9827
```



In [27]:

```
w_after = model_drop.get_weights()

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


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

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

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



7. Three Hidden layers (input = 784,number of neurons in layer 1 = 400,number of neurons in layer 2 = 300,number of neurons in layer 3 = 200,output = 10)

1. Number of neurons here are activation functions.
2. Here activation function used is 'relu' and optimizer used is 'adam'.
3. Number of epochs is 20 and Batch_size is 128.
4. We used our metric as 'accuracy'.

In [28]:

```
epochs3 = 20
model_relu = Sequential()
model_relu.add(Dense(400, activation='relu', input_shape=(input_dim,), kernel_initializer=keras.initializers.he_normal(seed=None)))
model_relu.add(Dense(300, activation='relu', kernel_initializer=keras.initializers.he_normal(seed=None)))
model_relu.add(Dense(200, activation='relu', kernel_initializer=keras.initializers.he_normal(seed=None)))
model_relu.add(Dense(output_dim, activation='softmax'))

print(model_relu.summary())

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

history = model_relu.fit(X_train, Y_train, batch_size=batch_size, epochs=epochs3, verbose=1, validation_data=(X_test, Y_test))
```

```
Model: "sequential_4"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_8 (Dense)              (None, 400)               314000    
_________________________________________________________________
dense_9 (Dense)              (None, 300)               120300    
_________________________________________________________________
dense_10 (Dense)             (None, 200)               60200     
_________________________________________________________________
dense_11 (Dense)             (None, 10)                2010      
=================================================================
Total params: 496,510
Trainable params: 496,510
Non-trainable params: 0
_________________________________________________________________
None
```

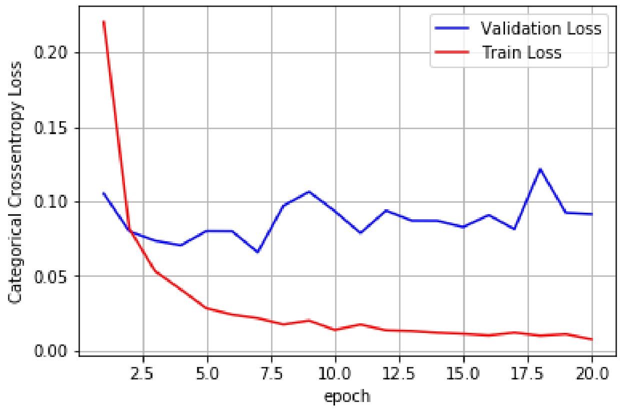
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 3s 43us/step - loss: 0.2204 - acc: 0.9349 -
val_loss: 0.1051 - val_acc: 0.9668
Epoch 2/20
60000/60000 [==============================] - 2s 36us/step - loss: 0.0815 - acc: 0.9746 -
val_loss: 0.0799 - val_acc: 0.9742
Epoch 3/20
60000/60000 [==============================] - 2s 37us/step - loss: 0.0532 - acc: 0.9830 -
val_loss: 0.0736 - val_acc: 0.9783
Epoch 4/20
60000/60000 [==============================] - 2s 38us/step - loss: 0.0409 - acc: 0.9868 -
val_loss: 0.0704 - val_acc: 0.9803
Epoch 5/20
60000/60000 [==============================] - 2s 37us/step - loss: 0.0283 - acc: 0.9909 -
val_loss: 0.0800 - val_acc: 0.9765
Epoch 6/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.0240 - acc: 0.9924 -
val_loss: 0.0800 - val_acc: 0.9774
Epoch 7/20
60000/60000 [==============================] - 2s 38us/step - loss: 0.0216 - acc: 0.9932 -
val_loss: 0.0658 - val_acc: 0.9830
Epoch 8/20
60000/60000 [==============================] - 2s 38us/step - loss: 0.0174 - acc: 0.9942 -
val_loss: 0.0970 - val_acc: 0.9763
Epoch 9/20
60000/60000 [==============================] - 2s 37us/step - loss: 0.0200 - acc: 0.9934 -
val_loss: 0.1064 - val_acc: 0.9749
Epoch 10/20
60000/60000 [==============================] - 2s 37us/step - loss: 0.0137 - acc: 0.9953 -
val_loss: 0.0935 - val_acc: 0.9772
Epoch 11/20
60000/60000 [==============================] - 2s 37us/step - loss: 0.0173 - acc: 0.9947 -
val_loss: 0.0787 - val_acc: 0.9807
Epoch 12/20
60000/60000 [==============================] - 2s 36us/step - loss: 0.0134 - acc: 0.9957 -
val_loss: 0.0938 - val_acc: 0.9787
Epoch 13/20
60000/60000 [==============================] - 2s 36us/step - loss: 0.0129 - acc: 0.9958 -
val_loss: 0.0871 - val_acc: 0.9798
Epoch 14/20
60000/60000 [==============================] - 2s 37us/step - loss: 0.0118 - acc: 0.9962 -
val_loss: 0.0870 - val_acc: 0.9790
Epoch 15/20
60000/60000 [==============================] - 2s 37us/step - loss: 0.0111 - acc: 0.9963 -
val_loss: 0.0827 - val_acc: 0.9815
Epoch 16/20
60000/60000 [==============================] - 2s 37us/step - loss: 0.0100 - acc: 0.9969 -
val_loss: 0.0908 - val_acc: 0.9807
Epoch 17/20
60000/60000 [==============================] - 2s 37us/step - loss: 0.0119 - acc: 0.9964 -
val_loss: 0.0813 - val_acc: 0.9820
Epoch 18/20
60000/60000 [==============================] - 2s 38us/step - loss: 0.0098 - acc: 0.9972 -
val_loss: 0.1216 - val_acc: 0.9754
Epoch 19/20
60000/60000 [==============================] - 2s 36us/step - loss: 0.0109 - acc: 0.9965 -
val_loss: 0.0924 - val_acc: 0.9812
Epoch 20/20
60000/60000 [==============================] - 2s 36us/step - loss: 0.0074 - acc: 0.9978 -
val_loss: 0.0914 - val_acc: 0.9818
```

In [29]:

```
score1 = model_relu.evaluate(X_train, Y_train, verbose=0)
print('Train score:', score1[0])
print('Train accuracy:', score1[1])
print("################################################")
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
```

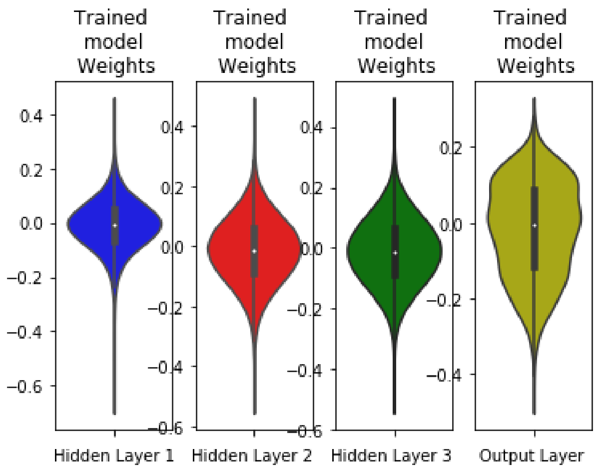
```
x = list(range(1,epochs3+1))

# 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)
```

```
Train score: 0.006188314759214101
Train accuracy: 0.9981166666666667
#############################################
Test score: 0.09144958206801962
Test accuracy: 0.9818
```



In [30]:

```
w_after = model_relu.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(1, 4, 1)
plt.title("Trained \n model \n Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

plt.subplot(1, 4, 2)
plt.title("Trained \n model \n Weights")
ax = sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden Layer 2 ')

plt.subplot(1, 4, 3)
plt.title("Trained \n model \n Weights")
ax = sns.violinplot(y=h3_w, color='g')
plt.xlabel('Hidden Layer 3 ')

plt.subplot(1, 4, 4)
plt.title("Trained \n model \n Weights")
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output Layer ')
plt.show()
```



8. Three Hidden layers (input = 784,number of neurons in layer 1 = 400,number of neurons in layer 2 = 300,number of neurons in layer 3 = 200,output = 10) with batch normalization and dropout

1. Number of neurons here are activation functions.
2. Here activation function used is 'relu' and optimizer used is 'adam'.
3. Number of epochs is 20 and Batch_size is 128.
4. We used our metric as 'accuracy'.
5. We used Batch normalization and dropout at Layer2 and Layer3.
6. Dropout rate is 0.5

In [31]:

```
model_drop = Sequential()

model_drop.add(Dense(400, activation='relu', input_shape=(input_dim,), kernel_initializer=keras.initializers.he_uniform(seed=None)))
# model_drop.add(BatchNormalization())
# model_drop.add(Dropout(0.5))

model_drop.add(Dense(300, activation='relu', kernel_initializer=keras.initializers.he_uniform(seed=None)) )
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

model_drop.add(Dense(200, activation='relu', kernel_initializer=keras.initializers.he_uniform(seed=None)) )
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

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


model_drop.summary()
```

```
Model: "sequential_5"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_12 (Dense)             (None, 400)               314000
_________________________________________________________________
dense_13 (Dense)             (None, 300)               120300
_________________________________________________________________
batch_normalization_3 (Batch (None, 300)               1200
_________________________________________________________________
dropout_3 (Dropout)          (None, 300)               0
_________________________________________________________________
dense_14 (Dense)             (None, 200)               60200
_________________________________________________________________
batch_normalization_4 (Batch (None, 200)               800
```

```
_________________________________________________________________
dropout_4 (Dropout)          (None, 200)               0
_________________________________________________________________
dense_15 (Dense)             (None, 10)                2010
=================================================================
Total params: 498,510
Trainable params: 497,510
Non-trainable params: 1,000
_________________________________________________________________
```

In [32]:

```
epoch4 = 20
model_drop.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=epoch4, verbose=1, validat
ion_data=(X_test, Y_test))
```

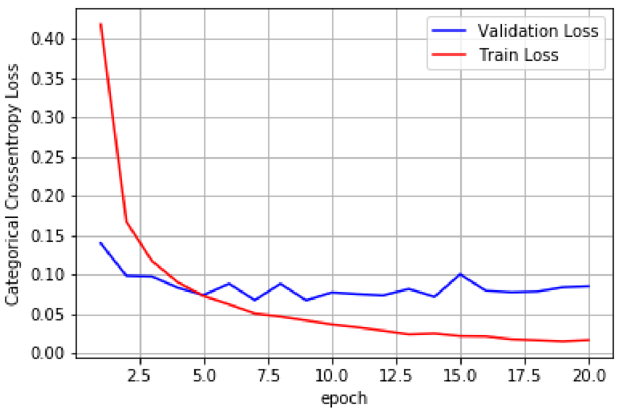
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 4s 73us/step - loss: 0.4179 - acc: 0.8753 -
val_loss: 0.1395 - val_acc: 0.9564
Epoch 2/20
60000/60000 [==============================] - 4s 60us/step - loss: 0.1670 - acc: 0.9496 -
val_loss: 0.0982 - val_acc: 0.9683
Epoch 3/20
60000/60000 [==============================] - 4s 59us/step - loss: 0.1169 - acc: 0.9642 -
val_loss: 0.0973 - val_acc: 0.9691
Epoch 4/20
60000/60000 [==============================] - 4s 60us/step - loss: 0.0901 - acc: 0.9726 -
val_loss: 0.0831 - val_acc: 0.9745
Epoch 5/20
60000/60000 [==============================] - 3s 58us/step - loss: 0.0726 - acc: 0.9777 -
val_loss: 0.0735 - val_acc: 0.9770
Epoch 6/20
60000/60000 [==============================] - 4s 59us/step - loss: 0.0618 - acc: 0.9813 -
val_loss: 0.0882 - val_acc: 0.9750
Epoch 7/20
60000/60000 [==============================] - 4s 59us/step - loss: 0.0502 - acc: 0.9841 -
val_loss: 0.0670 - val_acc: 0.9818
Epoch 8/20
60000/60000 [==============================] - 3s 58us/step - loss: 0.0464 - acc: 0.9853 -
val_loss: 0.0881 - val_acc: 0.9773
Epoch 9/20
60000/60000 [==============================] - 4s 59us/step - loss: 0.0415 - acc: 0.9870 -
val_loss: 0.0668 - val_acc: 0.9822
Epoch 10/20
60000/60000 [==============================] - 3s 58us/step - loss: 0.0364 - acc: 0.9887 -
val_loss: 0.0769 - val_acc: 0.9793
Epoch 11/20
60000/60000 [==============================] - 4s 59us/step - loss: 0.0327 - acc: 0.9896 -
val_loss: 0.0747 - val_acc: 0.9815
Epoch 12/20
60000/60000 [==============================] - 4s 59us/step - loss: 0.0283 - acc: 0.9911 -
val_loss: 0.0731 - val_acc: 0.9806
Epoch 13/20
60000/60000 [==============================] - 4s 60us/step - loss: 0.0237 - acc: 0.9923 -
val_loss: 0.0815 - val_acc: 0.9800
Epoch 14/20
60000/60000 [==============================] - 3s 58us/step - loss: 0.0248 - acc: 0.9918 -
val_loss: 0.0713 - val_acc: 0.9815
Epoch 15/20
60000/60000 [==============================] - 4s 59us/step - loss: 0.0215 - acc: 0.9934 -
val_loss: 0.1002 - val_acc: 0.9772
Epoch 16/20
60000/60000 [==============================] - 4s 60us/step - loss: 0.0211 - acc: 0.9933 -
val_loss: 0.0793 - val_acc: 0.9815
Epoch 17/20
60000/60000 [==============================] - 4s 59us/step - loss: 0.0174 - acc: 0.9943 -
val_loss: 0.0771 - val_acc: 0.9825
Epoch 18/20
60000/60000 [==============================] - 4s 61us/step - loss: 0.0162 - acc: 0.9948 -
val_loss: 0.0781 - val_acc: 0.9817
Epoch 19/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.0148 - acc: 0.9950 -
val_loss: 0.0837 - val_acc: 0.9811
```

```
val_loss: 0.0837 - val_acc: 0.9811
Epoch 20/20
60000/60000 [==============================] - 3s 58us/step - loss: 0.0164 - acc: 0.9944 -
val_loss: 0.0849 - val_acc: 0.9805
```

In [33]:

```
score1 = model_drop.evaluate(X_train, Y_train, verbose=0)
print('Train score:', score1[0])
print('Train accuracy:', score1[1])
print("###############################################")
score = model_drop.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

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

# list of epoch numbers
x = list(range(1,epoch4+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)
```

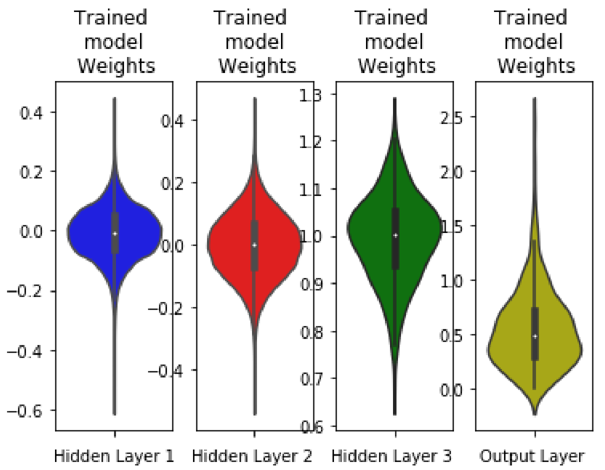
```
Train score: 0.005323547289566622
Train accuracy: 0.9979833333333333
###############################################
Test score: 0.08492160267545477
Test accuracy: 0.9805
```



In [35]:

```
w_after = model_drop.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(1, 4, 1)
plt.title("Trained \n model \n Weights")
```

```
plt.title("Trained \n model \n Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

plt.subplot(1, 4, 2)
plt.title("Trained \n model \n Weights")
ax = sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden Layer 2 ')

plt.subplot(1, 4, 3)
plt.title("Trained \n model \n Weights")
ax = sns.violinplot(y=h3_w, color='g')
plt.xlabel('Hidden Layer 3 ')

plt.subplot(1, 4, 4)
plt.title("Trained \n model \n Weights")
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output Layer ')
plt.show()
```



9. Three Hidden layers (input = 784,number of neurons in layer 1 = 400,number of neurons in layer 2 = 300,number of neurons in layer 3 = 200,output = 10) with batch normalization and dropout

1. Number of neurons here are activation functions.
2. Here activation function used is 'relu' and optimizer used is 'adam'.
3. Number of epochs is 5 and Batch_size is 128.
4. We used our metric as 'accuracy'.
5. We used Batch normalization and dropout at Layer2 and Layer3.
6. Dropout rate is 0.5

In [36]:

```
model_drop = Sequential()

model_drop.add(Dense(400, activation='relu', input_shape=(input_dim,), kernel_initializer=keras.ini
tializers.he_uniform(seed=None)))
# model_drop.add(BatchNormalization())
# model_drop.add(Dropout(0.5))

model_drop.add(Dense(300, activation='relu', kernel_initializer=keras.initializers.he_uniform(seed=
None)) )
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

model_drop.add(Dense(200, activation='relu', kernel_initializer=keras.initializers.he_uniform(seed=
None)) )
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

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

```
model_drop.summary()
```

```
Model: "sequential_6"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_16 (Dense)             (None, 400)               314000    
_________________________________________________________________
dense_17 (Dense)             (None, 300)               120300    
_________________________________________________________________
batch_normalization_5 (Batch (None, 300)               1200      
_________________________________________________________________
dropout_5 (Dropout)          (None, 300)               0         
_________________________________________________________________
dense_18 (Dense)             (None, 200)               60200     
_________________________________________________________________
batch_normalization_6 (Batch (None, 200)               800       
_________________________________________________________________
dropout_6 (Dropout)          (None, 200)               0         
_________________________________________________________________
dense_19 (Dense)             (None, 10)                2010      
=================================================================
Total params: 498,510
Trainable params: 497,510
Non-trainable params: 1,000
_________________________________________________________________
```

In [37]:

```
epoch5 = 5
model_drop.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=epoch5, verbose=1, validat
ion_data=(X_test, Y_test))
```

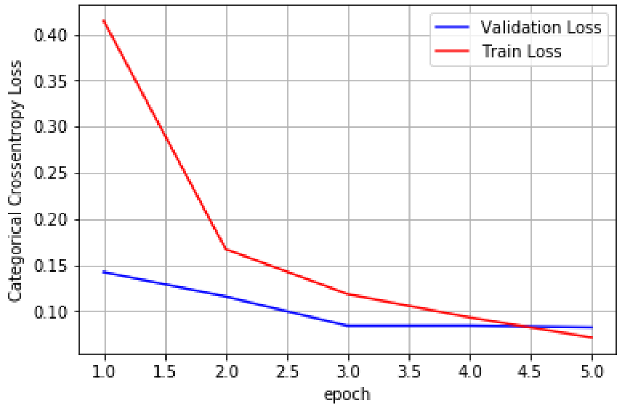
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/5
60000/60000 [==============================] - 5s 76us/step - loss: 0.4143 - acc: 0.8737 - 
val_loss: 0.1421 - val_acc: 0.9558
Epoch 2/5
60000/60000 [==============================] - 4s 59us/step - loss: 0.1671 - acc: 0.9495 - 
val_loss: 0.1156 - val_acc: 0.9628
Epoch 3/5
60000/60000 [==============================] - 4s 59us/step - loss: 0.1182 - acc: 0.9649 - 
val_loss: 0.0839 - val_acc: 0.9734
Epoch 4/5
60000/60000 [==============================] - 4s 59us/step - loss: 0.0931 - acc: 0.9718 - 
val_loss: 0.0840 - val_acc: 0.9735
Epoch 5/5
60000/60000 [==============================] - 4s 61us/step - loss: 0.0712 - acc: 0.9774 - 
val_loss: 0.0823 - val_acc: 0.9751
```

In [38]:

```
score1 = model_drop.evaluate(X_train, Y_train, verbose=0)
print('Train score:', score1[0])
print('Train accuracy:', score1[1])
print("##############################################")
score = model_drop.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

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

# list of epoch numbers
x = list(range(1,epoch5+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))
```

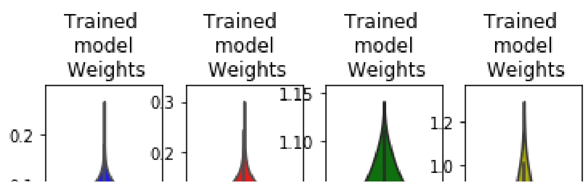
```
# we will get val_loss and val_acc only when you pass the paramter validation_data
# val_loss : validation loss
# val_acc : validation accuracy

# 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)
```

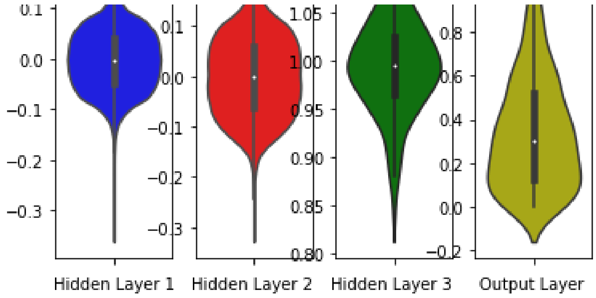
```
Train score: 0.03955110224107824
Train accuracy: 0.9873833333333333
##############################################
Test score: 0.08230718570513418
Test accuracy: 0.9751
```



In [39]:

```
w_after = model_drop.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(1, 4, 1)
plt.title("Trained \n model \n Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

plt.subplot(1, 4, 2)
plt.title("Trained \n model \n Weights")
ax = sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden Layer 2 ')

plt.subplot(1, 4, 3)
plt.title("Trained \n model \n Weights")
ax = sns.violinplot(y=h3_w, color='g')
plt.xlabel('Hidden Layer 3 ')

plt.subplot(1, 4, 4)
plt.title("Trained \n model \n Weights")
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output Layer ')
plt.show()
```





10. Five Hidden layers (input = 784,number of neurons in layer 1 = 450,number of neurons in layer 2 = 350,number of neurons in layer 3 = 250,number of neurons in layer 4 = 150,number of neurons in layer 5 = 50,output = 10)

1. Number of neurons here are activation functions.
2. Here activation function used is 'relu' and optimizer used is 'adam'.
3. Number of epochs is 20 and Batch_size is 128.
4. We used our metric as 'accuracy'.

In [40]:

```
model = Sequential()

model.add(Dense(450, activation='relu', input_shape=(input_dim,), kernel_initializer=keras.initiali
zers.he_uniform(seed=None)))

model.add(Dense(350, activation='relu', kernel_initializer=keras.initializers.he_uniform(seed=None)
) )

model.add(Dense(250, activation='relu', kernel_initializer=keras.initializers.he_uniform(seed=None)
) )

model.add(Dense(150, activation='relu', kernel_initializer=keras.initializers.he_uniform(seed=None)
) )

model.add(Dense(50, activation='relu',
kernel_initializer=keras.initializers.he_uniform(seed=None)) )

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


model.summary()
```

```
Model: "sequential_7"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_20 (Dense)             (None, 450)               353250
_________________________________________________________________
dense_21 (Dense)             (None, 350)               157850
_________________________________________________________________
dense_22 (Dense)             (None, 250)               87750
_________________________________________________________________
dense_23 (Dense)             (None, 150)               37650
_________________________________________________________________
dense_24 (Dense)             (None, 50)                7550
_________________________________________________________________
dense_25 (Dense)             (None, 10)                510
=================================================================
Total params: 644,560
Trainable params: 644,560
Non-trainable params: 0
_________________________________________________________________
```

In [41]:

```
epoch6 = 20
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history = model.fit(X_train, Y_train, batch_size=batch_size, epochs=epoch6, verbose=1, validation_d
ata=(X_test, Y_test))
```

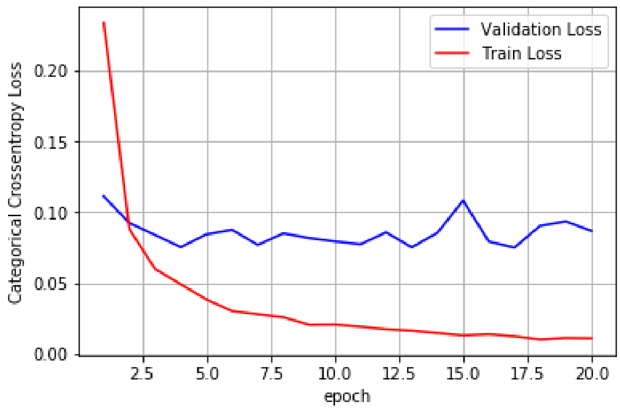
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.2334 - acc: 0.9291 -
val_loss: 0.1112 - val_acc: 0.9652
Epoch 2/20
60000/60000 [==============================] - 3s 43us/step - loss: 0.0881 - acc: 0.9732 -
val_loss: 0.0925 - val_acc: 0.9705
Epoch 3/20
60000/60000 [==============================] - 3s 42us/step - loss: 0.0601 - acc: 0.9816 -
val_loss: 0.0840 - val_acc: 0.9737
Epoch 4/20
60000/60000 [==============================] - 3s 43us/step - loss: 0.0493 - acc: 0.9841 -
val_loss: 0.0754 - val_acc: 0.9755
Epoch 5/20
60000/60000 [==============================] - 3s 43us/step - loss: 0.0386 - acc: 0.9876 -
val_loss: 0.0844 - val_acc: 0.9779
Epoch 6/20
60000/60000 [==============================] - 3s 43us/step - loss: 0.0304 - acc: 0.9904 -
val_loss: 0.0876 - val_acc: 0.9771
Epoch 7/20
60000/60000 [==============================] - 3s 43us/step - loss: 0.0282 - acc: 0.9908 -
val_loss: 0.0770 - val_acc: 0.9791
Epoch 8/20
60000/60000 [==============================] - 2s 41us/step - loss: 0.0261 - acc: 0.9917 -
val_loss: 0.0851 - val_acc: 0.9774
Epoch 9/20
60000/60000 [==============================] - 3s 42us/step - loss: 0.0208 - acc: 0.9938 -
val_loss: 0.0818 - val_acc: 0.9810
Epoch 10/20
60000/60000 [==============================] - 3s 42us/step - loss: 0.0209 - acc: 0.9934 -
val_loss: 0.0795 - val_acc: 0.9798
Epoch 11/20
60000/60000 [==============================] - 3s 42us/step - loss: 0.0194 - acc: 0.9940 -
val_loss: 0.0774 - val_acc: 0.9805
Epoch 12/20
60000/60000 [==============================] - 3s 42us/step - loss: 0.0176 - acc: 0.9946 -
val_loss: 0.0859 - val_acc: 0.9796
Epoch 13/20
60000/60000 [==============================] - 3s 43us/step - loss: 0.0166 - acc: 0.9946 -
val_loss: 0.0753 - val_acc: 0.9806
Epoch 14/20
60000/60000 [==============================] - 3s 43us/step - loss: 0.0150 - acc: 0.9949 -
val_loss: 0.0856 - val_acc: 0.9792
Epoch 15/20
60000/60000 [==============================] - 3s 42us/step - loss: 0.0133 - acc: 0.9957 -
val_loss: 0.1083 - val_acc: 0.9776
Epoch 16/20
60000/60000 [==============================] - 2s 40us/step - loss: 0.0141 - acc: 0.9957 -
val_loss: 0.0794 - val_acc: 0.9829
Epoch 17/20
60000/60000 [==============================] - 2s 41us/step - loss: 0.0126 - acc: 0.9965 -
val_loss: 0.0751 - val_acc: 0.9821
Epoch 18/20
60000/60000 [==============================] - 3s 42us/step - loss: 0.0104 - acc: 0.9968 -
val_loss: 0.0905 - val_acc: 0.9804
Epoch 19/20
60000/60000 [==============================] - 3s 42us/step - loss: 0.0114 - acc: 0.9967 -
val_loss: 0.0935 - val_acc: 0.9800
Epoch 20/20
60000/60000 [==============================] - 3s 42us/step - loss: 0.0112 - acc: 0.9969 -
val_loss: 0.0869 - val_acc: 0.9823
```

In [42]:

```
score1 = model.evaluate(X_train, Y_train, verbose=0)
print('Train score:', score1[0])
print('Train accuracy:', score1[1])
print("############################################")
score = model.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[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,epoch6+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)
```

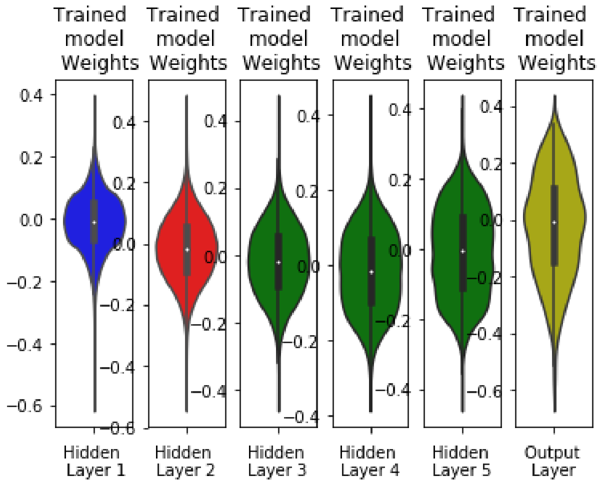
```
Train score: 0.005956138463119047
Train accuracy: 0.9984
#############################################
Test score: 0.0868614871434289
Test accuracy: 0.9823
```



In [43]:

```
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)
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(1, 6, 1)
plt.title("Trained \n model \n  Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden \n Layer 1')

plt.subplot(1, 6, 2)
plt.title("Trained \n model \n Weights")
ax = sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden \n Layer 2 ')

plt.subplot(1, 6, 3)
plt.title("Trained \n model \n Weights")
ax = sns.violinplot(y=h3_w, color='g')
```

```
plt.xlabel('Hidden \n Layer 3 ')

plt.subplot(1, 6, 4)
plt.title("Trained \n model \n Weights")
ax = sns.violinplot(y=h4_w, color='g')
plt.xlabel('Hidden \n Layer 4 ')

plt.subplot(1, 6, 5)
plt.title("Trained \n model \n Weights")
ax = sns.violinplot(y=h5_w, color='g')
plt.xlabel('Hidden \n Layer 5 ')


plt.subplot(1, 6, 6)
plt.title("Trained \n model \n Weights")
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output \n Layer ')
plt.show()
```



In [0]:

```

```

In [0]:

```

```

11. Five Hidden layers (input = 784,number of neurons in layer 1 = 450,number of neurons in layer 2 = 350,number of neurons in layer 3 = 250,number of neurons in layer 4 = 150,number of neurons in layer 5 = 50,output = 10) with batch normalization and dropout

1. Number of neurons here are activation functions.
2. Here activation function used is 'relu' and optimizer used is 'adam'.
3. Number of epochs is 20 and Batch_size is 128.
4. We used our metric as 'accuracy'.
5. We used Batch normalization and dropout at Layer2, Layer3,Layer4 and Layer5.
6. Dropout rate is 0.5

In [44]:

```
model_drop = Sequential()

model_drop.add(Dense(450, activation='relu', input_shape=(input_dim,), kernel_initializer=keras.ini
tializers.he_uniform(seed=None)))
# model_drop.add(BatchNormalization())
# model_drop.add(Dropout(0.5))
```

```
model_drop.add(Dense(350, activation='relu', kernel_initializer=keras.initializers.he_uniform(seed=None)) )
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

model_drop.add(Dense(250, activation='relu', kernel_initializer=keras.initializers.he_uniform(seed=None)) )
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

model_drop.add(Dense(150, activation='relu', kernel_initializer=keras.initializers.he_uniform(seed=None)) )
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

model_drop.add(Dense(50, activation='relu', kernel_initializer=keras.initializers.he_uniform(seed=None)) )
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

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


model_drop.summary()
```

```
Model: "sequential_8"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_26 (Dense)             (None, 450)               353250    
_________________________________________________________________
dense_27 (Dense)             (None, 350)               157850    
_________________________________________________________________
batch_normalization_7 (Batch (None, 350)               1400      
_________________________________________________________________
dropout_7 (Dropout)          (None, 350)               0         
_________________________________________________________________
dense_28 (Dense)             (None, 250)               87750     
_________________________________________________________________
batch_normalization_8 (Batch (None, 250)               1000      
_________________________________________________________________
dropout_8 (Dropout)          (None, 250)               0         
_________________________________________________________________
dense_29 (Dense)             (None, 150)               37650     
_________________________________________________________________
batch_normalization_9 (Batch (None, 150)               600       
_________________________________________________________________
dropout_9 (Dropout)          (None, 150)               0         
_________________________________________________________________
dense_30 (Dense)             (None, 50)                7550      
_________________________________________________________________
batch_normalization_10 (Batc (None, 50)                200       
_________________________________________________________________
dropout_10 (Dropout)         (None, 50)                0         
_________________________________________________________________
dense_31 (Dense)             (None, 10)                510       
=================================================================
Total params: 647,760
Trainable params: 646,160
Non-trainable params: 1,600
_________________________________________________________________
```

In [45]:

```
epoch7 = 20
model_drop.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=epoch7, verbose=1, validation_data=(X_test, Y_test))
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 7s 115us/step - loss: 0.8682 - acc: 0.7331 - val_loss: 0.2103 - val_acc: 0.9385
Epoch 2/20
```

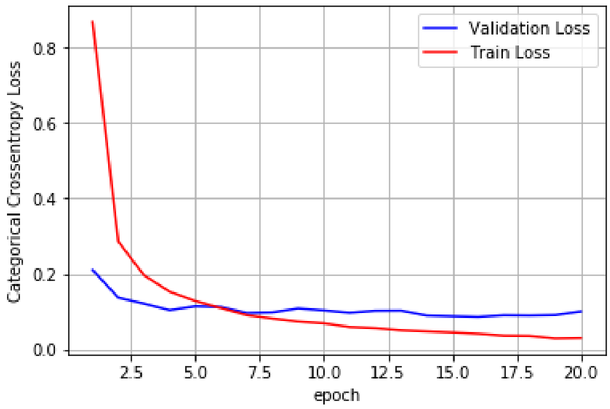
```
60000/60000 [==============================] - 5s 89us/step - loss: 0.2858 - acc: 0.9245 -
val_loss: 0.1370 - val_acc: 0.9604
Epoch 3/20
60000/60000 [==============================] - 5s 88us/step - loss: 0.1962 - acc: 0.9498 -
val_loss: 0.1211 - val_acc: 0.9689
Epoch 4/20
60000/60000 [==============================] - 5s 85us/step - loss: 0.1528 - acc: 0.9609 -
val_loss: 0.1039 - val_acc: 0.9728
Epoch 5/20
60000/60000 [==============================] - 5s 87us/step - loss: 0.1281 - acc: 0.9679 -
val_loss: 0.1142 - val_acc: 0.9704
Epoch 6/20
60000/60000 [==============================] - 5s 87us/step - loss: 0.1091 - acc: 0.9726 -
val_loss: 0.1123 - val_acc: 0.9719
Epoch 7/20
60000/60000 [==============================] - 5s 85us/step - loss: 0.0907 - acc: 0.9762 -
val_loss: 0.0962 - val_acc: 0.9767
Epoch 8/20
60000/60000 [==============================] - 5s 85us/step - loss: 0.0815 - acc: 0.9802 -
val_loss: 0.0979 - val_acc: 0.9778
Epoch 9/20
60000/60000 [==============================] - 5s 87us/step - loss: 0.0736 - acc: 0.9813 -
val_loss: 0.1084 - val_acc: 0.9760
Epoch 10/20
60000/60000 [==============================] - 5s 87us/step - loss: 0.0690 - acc: 0.9825 -
val_loss: 0.1031 - val_acc: 0.9755
Epoch 11/20
60000/60000 [==============================] - 5s 85us/step - loss: 0.0590 - acc: 0.9849 -
val_loss: 0.0969 - val_acc: 0.9779
Epoch 12/20
60000/60000 [==============================] - 5s 84us/step - loss: 0.0560 - acc: 0.9863 -
val_loss: 0.1021 - val_acc: 0.9791
Epoch 13/20
60000/60000 [==============================] - 5s 85us/step - loss: 0.0503 - acc: 0.9878 -
val_loss: 0.1025 - val_acc: 0.9781
Epoch 14/20
60000/60000 [==============================] - 5s 85us/step - loss: 0.0474 - acc: 0.9885 -
val_loss: 0.0896 - val_acc: 0.9807
Epoch 15/20
60000/60000 [==============================] - 5s 87us/step - loss: 0.0445 - acc: 0.9886 -
val_loss: 0.0877 - val_acc: 0.9823
Epoch 16/20
60000/60000 [==============================] - 5s 83us/step - loss: 0.0411 - acc: 0.9893 -
val_loss: 0.0859 - val_acc: 0.9821
Epoch 17/20
60000/60000 [==============================] - 5s 84us/step - loss: 0.0360 - acc: 0.9911 -
val_loss: 0.0904 - val_acc: 0.9804
Epoch 18/20
60000/60000 [==============================] - 5s 85us/step - loss: 0.0354 - acc: 0.9914 -
val_loss: 0.0897 - val_acc: 0.9806
Epoch 19/20
60000/60000 [==============================] - 5s 84us/step - loss: 0.0287 - acc: 0.9927 -
val_loss: 0.0909 - val_acc: 0.9813
Epoch 20/20
60000/60000 [==============================] - 5s 84us/step - loss: 0.0297 - acc: 0.9926 -
val_loss: 0.1003 - val_acc: 0.9800
```

In [46]:

```
score1 = model_drop.evaluate(X_train, Y_train, verbose=0)
print('Train score:', score1[0])
print('Train accuracy:', score1[1])
print("##############################################")
score = model_drop.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

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

# list of epoch numbers
x = list(range(1,epoch7+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)
```

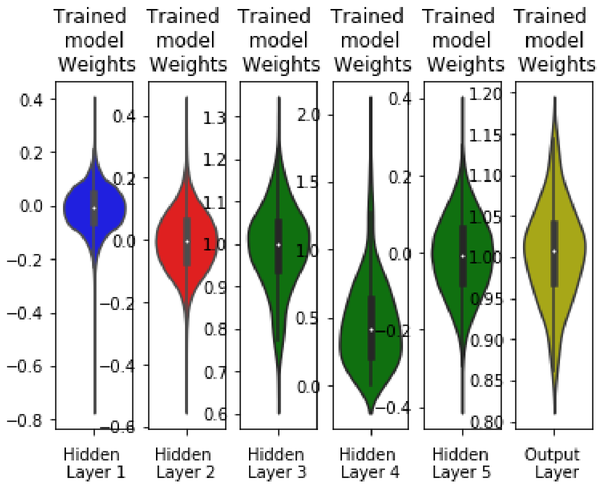
```
Train score: 0.009203571533679497
Train accuracy: 0.9973833333333333
#############################################
Test score: 0.10026836708746704
Test accuracy: 0.98
```



In [47]:

```
w_after = model_drop.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(1, 6, 1)
plt.title("Trained \n model \n Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden \n Layer 1')

plt.subplot(1, 6, 2)
plt.title("Trained \n model \n Weights")
ax = sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden \n Layer 2 ')

plt.subplot(1, 6, 3)
plt.title("Trained \n model \n Weights")
ax = sns.violinplot(y=h3_w, color='g')
plt.xlabel('Hidden \n Layer 3 ')

plt.subplot(1, 6, 4)
plt.title("Trained \n model \n Weights")
ax = sns.violinplot(y=h4_w, color='g')
plt.xlabel('Hidden \n Layer 4 ')

plt.subplot(1, 6, 5)
plt.title("Trained \n model \n Weights")
ax = sns.violinplot(y=h5_w, color='g')
plt.xlabel('Hidden \n Layer 5 ')
```

```
plt.subplot(1, 6, 6)
plt.title("Trained \n model \n Weights")
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output \n  Layer ')
plt.show()
```



12. Five Hidden layers (input = 784,number of neurons in layer 1 = 450,number of neurons in layer 2 = 350,number of neurons in layer 3 = 250,number of neurons in layer 4 = 150,number of neurons in layer 5 = 50,output = 10) with batch normalization a dropout

In [ ]:

```
1. Number of neurons here are activation functions.
2. Here activation function used is 'relu' and optimizer used is 'adam'.
3. Number of epochs is 10 and Batch_size is 128.
4. We used our metric as 'accuracy'.
5. We used Batch normalization and dropout at Layer2, Layer3,Layer4 and Layer5.
6. Dropout  rate is 0.5
```

In [48]:

```
model_drop = Sequential()

model_drop.add(Dense(450, activation='relu', input_shape=(input_dim,), kernel_initializer=keras.ini
tializers.he_uniform(seed=None)))
# model_drop.add(BatchNormalization())
# model_drop.add(Dropout(0.5))

model_drop.add(Dense(350, activation='relu', kernel_initializer=keras.initializers.he_uniform(seed=
None)) )
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

model_drop.add(Dense(250, activation='relu', kernel_initializer=keras.initializers.he_uniform(seed=
None)) )
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

model_drop.add(Dense(150, activation='relu', kernel_initializer=keras.initializers.he_uniform(seed=
None)) )
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

model_drop.add(Dense(50, activation='relu', kernel_initializer=keras.initializers.he_uniform(seed=N
one)) )
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

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

```
model_drop.summary()
```

```
Model: "sequential_9"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_32 (Dense)             (None, 450)               353250    
_________________________________________________________________
dense_33 (Dense)             (None, 350)               157850    
_________________________________________________________________
batch_normalization_11 (Batc (None, 350)               1400      
_________________________________________________________________
dropout_11 (Dropout)         (None, 350)               0         
_________________________________________________________________
dense_34 (Dense)             (None, 250)               87750     
_________________________________________________________________
batch_normalization_12 (Batc (None, 250)               1000      
_________________________________________________________________
dropout_12 (Dropout)         (None, 250)               0         
_________________________________________________________________
dense_35 (Dense)             (None, 150)               37650     
_________________________________________________________________
batch_normalization_13 (Batc (None, 150)               600       
_________________________________________________________________
dropout_13 (Dropout)         (None, 150)               0         
_________________________________________________________________
dense_36 (Dense)             (None, 50)                7550      
_________________________________________________________________
batch_normalization_14 (Batc (None, 50)                200       
_________________________________________________________________
dropout_14 (Dropout)         (None, 50)                0         
_________________________________________________________________
dense_37 (Dense)             (None, 10)                510       
=================================================================
Total params: 647,760
Trainable params: 646,160
Non-trainable params: 1,600
_________________________________________________________________
```

In [49]:

```
epoch8 = 10
model_drop.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=epoch8, verbose=1, validat
ion_data=(X_test, Y_test))
```

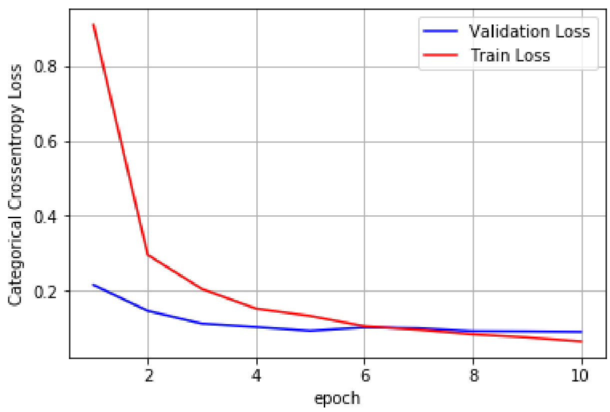
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/10
60000/60000 [==============================] - 7s 121us/step - loss: 0.9092 - acc: 0.7260 - 
val_loss: 0.2156 - val_acc: 0.9364
Epoch 2/10
60000/60000 [==============================] - 5s 87us/step - loss: 0.2963 - acc: 0.9228 - 
val_loss: 0.1467 - val_acc: 0.9598
Epoch 3/10
60000/60000 [==============================] - 5s 86us/step - loss: 0.2050 - acc: 0.9485 - 
val_loss: 0.1126 - val_acc: 0.9692
Epoch 4/10
60000/60000 [==============================] - 5s 88us/step - loss: 0.1526 - acc: 0.9615 - 
val_loss: 0.1034 - val_acc: 0.9745
Epoch 5/10
60000/60000 [==============================] - 5s 86us/step - loss: 0.1331 - acc: 0.9668 - 
val_loss: 0.0933 - val_acc: 0.9755
Epoch 6/10
60000/60000 [==============================] - 5s 86us/step - loss: 0.1058 - acc: 0.9732 - 
val_loss: 0.1025 - val_acc: 0.9751
Epoch 7/10
60000/60000 [==============================] - 5s 87us/step - loss: 0.0960 - acc: 0.9761 - 
val_loss: 0.1004 - val_acc: 0.9756
Epoch 8/10
60000/60000 [==============================] - 5s 86us/step - loss: 0.0839 - acc: 0.9793 - 
val_loss: 0.0924 - val_acc: 0.9764
Epoch 9/10
```

```
Epoch 9/10
60000/60000 [==============================] - 5s 86us/step - loss: 0.0758 - acc: 0.9807 -
val_loss: 0.0918 - val_acc: 0.9769
Epoch 10/10
60000/60000 [==============================] - 5s 84us/step - loss: 0.0649 - acc: 0.9833 -
val_loss: 0.0906 - val_acc: 0.9790
```

In [50]:

```python
score1 = model_drop.evaluate(X_train, Y_train, verbose=0)
print('Train score:', score1[0])
print('Train accuracy:', score1[1])
print("###############################################")
score = model_drop.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

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

# list of epoch numbers
x = list(range(1,epoch8+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)
```

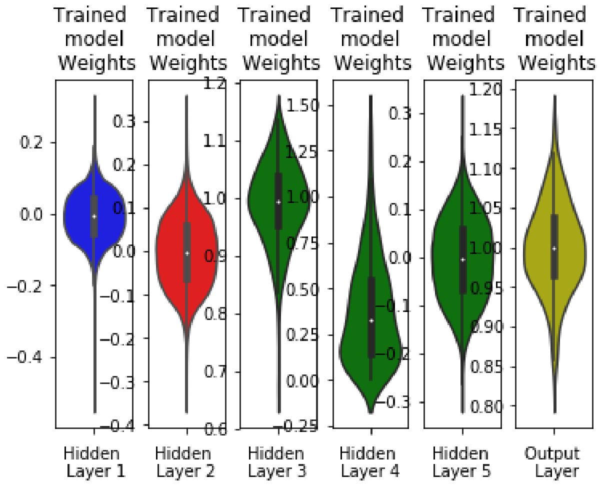
```
Train score: 0.029697504019745004
Train accuracy: 0.9924333333333333
##############################################
Test score: 0.09058548904829658
Test accuracy: 0.979
```



In [51]:

```python
w_after = model_drop.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(1, 6, 1)
plt.title("Trained \n model \n Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden \n Layer 1')

plt.subplot(1, 6, 2)
plt.title("Trained \n model \n Weights")
ax = sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden \n Layer 2 ')

plt.subplot(1, 6, 3)
plt.title("Trained \n model \n Weights")
ax = sns.violinplot(y=h3_w, color='g')
plt.xlabel('Hidden \n Layer 3 ')

plt.subplot(1, 6, 4)
plt.title("Trained \n model \n Weights")
ax = sns.violinplot(y=h4_w, color='g')
plt.xlabel('Hidden \n Layer 4 ')

plt.subplot(1, 6, 5)
plt.title("Trained \n model \n Weights")
ax = sns.violinplot(y=h5_w, color='g')
plt.xlabel('Hidden \n Layer 5 ')


plt.subplot(1, 6, 6)
plt.title("Trained \n model \n Weights")
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output \n  Layer ')
plt.show()
```



13. Hyperparameter Tuning 'epochs' and 'batch_size'

In [0]:

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

    model_drop.add(Dense(450, activation='relu', input_shape=(input_dim,), kernel_initializer=keras
.initializers.he_uniform(seed=None)))
    # model_drop.add(BatchNormalization())
    # model_drop.add(Dropout(0.5))

    model_drop.add(Dense(350, activation='relu', kernel_initializer=keras.initializers.he_uniform(s
eed=None)) )
    model_drop.add(BatchNormalization())
    model_drop.add(Dropout(0.5))

    model_drop.add(Dense(250, activation='relu', kernel_initializer=keras.initializers.he_uniform(s
eed=None)) )
    model_drop.add(BatchNormalization())
```

```
    model_drop.add(Dropout(0.5))

    model_drop.add(Dense(150, activation='relu', kernel_initializer=keras.initializers.he_uniform(s
eed=None)) )
    model_drop.add(BatchNormalization())
    model_drop.add(Dropout(0.5))

    model_drop.add(Dense(50, activation='relu', kernel_initializer=keras.initializers.he_uniform(se
ed=None)) )
    model_drop.add(BatchNormalization())
    model_drop.add(Dropout(0.5))

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



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

In [53]:

```
# https://machinelearningmastery.com/grid-search-hyperparameters-deep-learning-models-python-keras
/
from keras.wrappers.scikit_learn import KerasClassifier
from sklearn.model_selection import GridSearchCV

model_best = KerasClassifier(build_fn=best_hyperparameters, verbose=0)

epochs_best = [5,8]
batch_size_best = [200,300]

param_grid = dict(batch_size = batch_size_best,epochs = epochs_best)


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

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

```
/usr/local/lib/python3.6/dist-packages/sklearn/model_selection/_split.py:1978: FutureWarning: The
default value of cv will change from 3 to 5 in version 0.22. Specify it explicitly to silence this
warning.
  warnings.warn(CV_WARNING, FutureWarning)
```

In [54]:

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

```
Best: 0.981050 using {'batch_size': 200, 'epochs': 5}
0.981050 (0.006049) with: {'batch_size': 200, 'epochs': 5}
0.688733 (0.178250) with: {'batch_size': 200, 'epochs': 8}
0.398417 (0.070855) with: {'batch_size': 300, 'epochs': 5}
0.230083 (0.036925) with: {'batch_size': 300, 'epochs': 8}
```

14. Five Hidden layers (input = 784,number of neurons in layer 1 = 450,number of neurons in layer 2 = 350,number of neurons in layer 3 = 250,number of neurons in layer 4 = 150,number of neurons in layer 5 = 50,output = 10) with batch normalization a dropout

1. Number of neurons here are activation functions

1. Number of neurons here are activation functions.
2. Here activation function used is 'relu' and optimizer used is 'adam'.
3. Number of epochs is 5 and Batch_size is 200.
4. We used our metric as 'accuracy'.
5. We used Batch normalization and dropout at Layer2, Layer3,Layer4 and Layer5.
6. Dropout rate is 0.5

In [55]:

```
model_drop = Sequential()

model_drop.add(Dense(450, activation='relu', input_shape=(input_dim,), kernel_initializer=keras.initializers.he_uniform(seed=None)))
# model_drop.add(BatchNormalization())
# model_drop.add(Dropout(0.5))

model_drop.add(Dense(350, activation='relu', kernel_initializer=keras.initializers.he_uniform(seed=None)) )
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

model_drop.add(Dense(250, activation='relu', kernel_initializer=keras.initializers.he_uniform(seed=None)) )
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

model_drop.add(Dense(150, activation='relu', kernel_initializer=keras.initializers.he_uniform(seed=None)) )
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

model_drop.add(Dense(50, activation='relu', kernel_initializer=keras.initializers.he_uniform(seed=None)) )
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

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


model_drop.summary()
```

```
Model: "sequential_10"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_116 (Dense)            (None, 450)               353250    
_________________________________________________________________
dense_117 (Dense)            (None, 350)               157850    
_________________________________________________________________
batch_normalization_67 (Batc (None, 350)               1400      
_________________________________________________________________
dropout_67 (Dropout)         (None, 350)               0         
_________________________________________________________________
dense_118 (Dense)            (None, 250)               87750     
_________________________________________________________________
batch_normalization_68 (Batc (None, 250)               1000      
_________________________________________________________________
dropout_68 (Dropout)         (None, 250)               0         
_________________________________________________________________
dense_119 (Dense)            (None, 150)               37650     
_________________________________________________________________
batch_normalization_69 (Batc (None, 150)               600       
_________________________________________________________________
dropout_69 (Dropout)         (None, 150)               0         
_________________________________________________________________
dense_120 (Dense)            (None, 50)                7550      
_________________________________________________________________
batch_normalization_70 (Batc (None, 50)                200       
_________________________________________________________________
dropout_70 (Dropout)         (None, 50)                0         
_________________________________________________________________
dense_121 (Dense)            (None, 10)                510       
=================================================================
Total params: 647,760
Trainable params: 646,160
```

```
Non-trainable params: 1,600
_________________________________________________________________
```

In [56]:

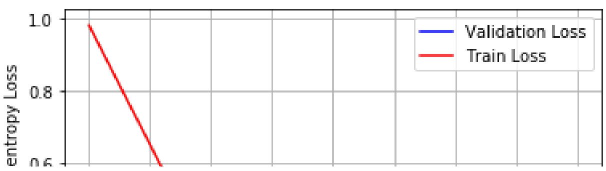
```python
epoch_best = 5
model_drop.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history = model_drop.fit(X_train, Y_train, batch_size= 200, epochs=epoch_best, verbose=1, validatio
n_data=(X_test, Y_test))
```

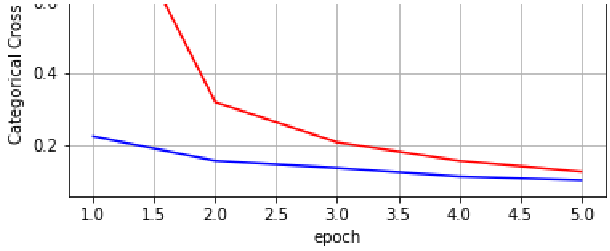
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/5
60000/60000 [==============================] - 26s 426us/step - loss: 0.9826 - acc: 0.6973 - val_l
oss: 0.2251 - val_acc: 0.9353
Epoch 2/5
60000/60000 [==============================] - 5s 75us/step - loss: 0.3202 - acc: 0.9156 -
val_loss: 0.1570 - val_acc: 0.9574
Epoch 3/5
60000/60000 [==============================] - 5s 75us/step - loss: 0.2085 - acc: 0.9472 -
val_loss: 0.1370 - val_acc: 0.9618
Epoch 4/5
60000/60000 [==============================] - 5s 76us/step - loss: 0.1570 - acc: 0.9606 -
val_loss: 0.1134 - val_acc: 0.9699
Epoch 5/5
60000/60000 [==============================] - 5s 76us/step - loss: 0.1267 - acc: 0.9689 -
val_loss: 0.1028 - val_acc: 0.9721
```

In [57]:

```python
score1 = model_drop.evaluate(X_train, Y_train, verbose=0)
print('Train score:', score1[0])
print('Train accuracy:', score1[1])
print("#############################################")
score = model_drop.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

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

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

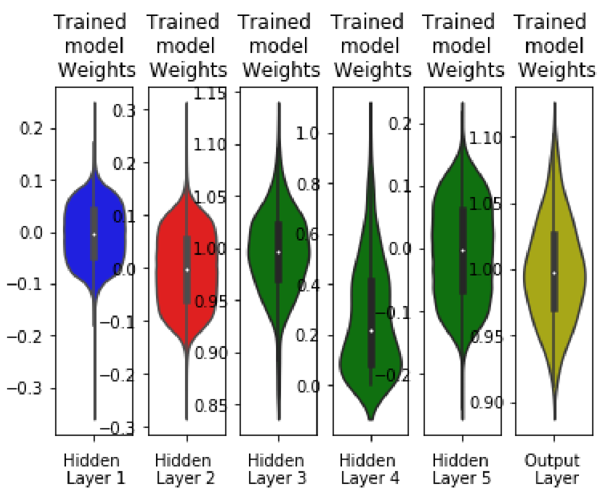
```
Train score: 0.055952023635990916
Train accuracy: 0.9843
#############################################
Test score: 0.10278879055995493
Test accuracy: 0.9721
```





In [58]:

```
w_after = model_drop.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(1, 6, 1)
plt.title("Trained \n model \n Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden \n Layer 1')

plt.subplot(1, 6, 2)
plt.title("Trained \n model \n Weights")
ax = sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden \n Layer 2 ')

plt.subplot(1, 6, 3)
plt.title("Trained \n model \n Weights")
ax = sns.violinplot(y=h3_w, color='g')
plt.xlabel('Hidden \n Layer 3 ')

plt.subplot(1, 6, 4)
plt.title("Trained \n model \n Weights")
ax = sns.violinplot(y=h4_w, color='g')
plt.xlabel('Hidden \n Layer 4 ')

plt.subplot(1, 6, 5)
plt.title("Trained \n model \n Weights")
ax = sns.violinplot(y=h5_w, color='g')
plt.xlabel('Hidden \n Layer 5 ')


plt.subplot(1, 6, 6)
plt.title("Trained \n model \n Weights")
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output \n  Layer ')
plt.show()
```



15. Conclusion

In [ ]:

```
adam and relu
```

In [9]:

```
# http://zetcode.com/python/prettytable/
from prettytable import PrettyTable

#If you get a ModuleNotFoundError error , install prettytable using: pip3 install prettytable

x = PrettyTable()

x.field_names = [ "Number of Layers", "Epoch","Batch size","BN and Dropout","Train Accuracy","Test Accuracy"]

x.add_row(["Two",40,128,"No",0.9997,0.9857])
x.add_row(["Two",20,128,"Yes at Layer1 and Layer2",0.9963,0.9827])
x.add_row(["Three",20,128,"No",0.9981,0.9818])
x.add_row(["Three",20,128,"Yes at Layer2 and Layer3",0.9979,0.9805])
x.add_row(["Three",5,128,"Yes at Layer2 and Layer3",0.9873,0.9751])
x.add_row(["Five",20,128,"No",0.9984,0.9823])
x.add_row(["Five",20,128,"Yes at Layer2,Layer3,Layer4 and Layer5",0.9973,0.98])
x.add_row(["Five",10,128,"Yes at Layer2,Layer3,Layer4 and Layer5",0.9924,0.979])
x.add_row(["Five",5,200,"Yes at Layer2,Layer3,Layer4 and Layer5",0.9843,0.9721])

print(x)
```

```
+------------------+-------+------------+----------------------------------------+----------------+----------------+
| Number of Layers | Epoch | Batch size |             BN and Dropout             | Train Accuracy | Test Accuracy |
+------------------+-------+------------+----------------------------------------+----------------+----------------+
|       Two        |   40  |    128     |                   No                   |     0.9997     | 0.9857    |
|       Two        |   20  |    128     |        Yes at Layer1 and Layer2        |     0.9963     | 0.9827    |
|      Three       |   20  |    128     |                   No                   |     0.9981     | 0.9818    |
|      Three       |   20  |    128     |        Yes at Layer2 and Layer3        |     0.9979     | 0.9805    |
|      Three       |   5   |    128     |        Yes at Layer2 and Layer3        |     0.9873     | 0.9751    |
|       Five       |   20  |    128     |                   No                   |     0.9984     | 0.9823    |
|       Five       |   20  |    128     | Yes at Layer2,Layer3,Layer4 and Layer5 |     0.9973     | 0.98     |
|       Five       |   10  |    128     | Yes at Layer2,Layer3,Layer4 and Layer5 |     0.9924     | 0.979     |
|       Five       |   5   |    200     | Yes at Layer2,Layer3,Layer4 and Layer5 |     0.9843     | 0.9721    |
+------------------+-------+------------+----------------------------------------+----------------+----------------+
```

In [ ]:

In [ ]: