In [1]:

```
from keras.utils import np_utils
from keras.datasets import mnist
import seaborn as sns
from keras.initializers import RandomNormal
```

```
Using TensorFlow backend.
```

In [0]:

```
%matplotlib inline
import matplotlib.pyplot as plt
import numpy as np
import time

def plt_dynamic(x, vy, ty, ax, colors=['b']):
    ax.plot(x, vy, 'b', label="Validation Loss")
    ax.plot(x, ty, 'r', label="Train Loss")
    plt.legend()
    plt.grid()
    fig.canvas.draw()
```

In [3]:

```
#splitting the data into train and test
(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]:

```
#train and test data shape and image shpae
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 [6]:

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

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

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

In [7]:

```
# An example data point
```

```
print(X_train[0])
```

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

In [0]:

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

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

In [9]:

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

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

```
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.01176471 0.07058824 0.07058824 0.07058824
0.49411765 0.53333333 0.68627451 0.10196078 0.65098039 1.
0.96862745 0.49803922 0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.11764706 0.14117647 0.36862745 0.60392157
0.66666667 0.99215686 0.99215686 0.99215686 0.99215686 0.99215686
0.88235294 0.6745098  0.99215686 0.94901961 0.76470588 0.25098039
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.19215686
0.93333333 0.99215686 0.99215686 0.99215686 0.99215686 0.99215686
0.99215686 0.99215686 0.99215686 0.98431373 0.36470588 0.32156863
0.32156863 0.21960784 0.15294118 0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.07058824 0.85882353 0.99215686
0.99215686 0.99215686 0.99215686 0.99215686 0.77647059 0.71372549
0.96862745 0.94509804 0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.31372549 0.61176471 0.41960784 0.99215686
0.99215686 0.80392157 0.04313725 0.         0.16862745 0.60392157
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.05490196 0.00392157 0.60392157 0.99215686 0.35294118
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.54509804 0.99215686 0.74509804 0.00784314 0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.04313725
0.74509804 0.99215686 0.2745098  0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.1372549  0.94509804
0.88235294 0.62745098 0.42352941 0.00392157 0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.31764706 0.94117647 0.99215686
0.99215686 0.46666667 0.09803922 0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.17647059 0.72941176 0.99215686 0.99215686
0.58823529 0.10588235 0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.0627451  0.36470588 0.98823529 0.99215686 0.73333333
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.97647059 0.99215686 0.97647059 0.25098039 0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.18039216 0.50980392 0.71764706 0.99215686
0.99215686 0.81176471 0.00784314 0.         0.         0.
0.         0.         0.         0.         0.         0.
0.         0.         0.         0.         0.         0.
```

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

In [10]:

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

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

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

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

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

In [0]:

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



# https://gist.github.com/greydanus/f6eee59eaf1d90fcb3b534a25362cea4
# https://stackoverflow.com/a/14434334
# this function is used to update the plots for each epoch and error
def plt_dynamic(x, vy, ty, ax, colors=['b']):
    ax.plot(x, vy, 'b', label="Validation Loss")
    ax.plot(x, ty, 'r', label="Train Loss")
```

```
    plt.legend()
    plt.grid()
    fig.canvas.draw()
```

In [0]:

```
# some model parameters
#output size
output_dim = 10
#input size
input_dim = X_train.shape[1]
#batch input size
batch_size = 128
#No of epochs
nb_epoch = 20
```

In [13]:

```
print('Columsn :',X_train.shape[1],'Rows :',X_train.shape[0])
```

```
Columsn : 784 Rows : 60000
```

Applied various types of architecture with different drop rates with different optimizers and different normalization and drop out at different layers

2 Layer architecture With Batch Normalization and Dropout

In [14]:

```
model_relu = Sequential()
#layer-1
model_relu.add(Dense(500, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNor
mal(mean=0.0, stddev=0.039, seed=None)))
#adding batch normalization
model_relu.add(BatchNormalization())
#addding dropout rate
model_relu.add(Dropout(0.5))
#layer-2
model_relu.add(Dense(200, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.039
, seed=None)))
#adding batch noramalization
model_relu.add(BatchNormalization())
#adding drop out rate
model_relu.add(Dropout(0.5))

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


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

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

```
WARNING: Logging before flag parsing goes to stderr.
W0829 13:26:52.092908 140021963048832 deprecation_wrapper.py:119] From
/usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:74: The name
tf.get_default_graph is deprecated. Please use tf.compat.v1.get_default_graph instead.

W0829 13:26:52.129713 140021963048832 deprecation_wrapper.py:119] From
/usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:517: The name
tf.placeholder is deprecated. Please use tf.compat.v1.placeholder instead.

W0829 13:26:52.140062 140021963048832 deprecation_wrapper.py:119] From
/usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:4115: The name
tf.random_normal is deprecated. Please use tf.random.normal instead.

W0829 13:26:52.245176 140021963048832 deprecation_wrapper.py:119] From
/usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:133: The name
```

```
/usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:133: The name
tf.placeholder_with_default is deprecated. Please use tf.compat.v1.placeholder_with_default instea
d.

W0829 13:26:52.271583 140021963048832 deprecation.py:506] From /usr/local/lib/python3.6/dist-
packages/keras/backend/tensorflow_backend.py:3445: 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`.
W0829 13:26:52.411946 140021963048832 deprecation_wrapper.py:119] From
/usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:4138: The name
tf.random_uniform is deprecated. Please use tf.random.uniform instead.

W0829 13:26:52.428584 140021963048832 deprecation_wrapper.py:119] From
/usr/local/lib/python3.6/dist-packages/keras/optimizers.py:790: The name tf.train.Optimizer is dep
recated. Please use tf.compat.v1.train.Optimizer instead.

W0829 13:26:52.576616 140021963048832 deprecation.py:323] 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
```

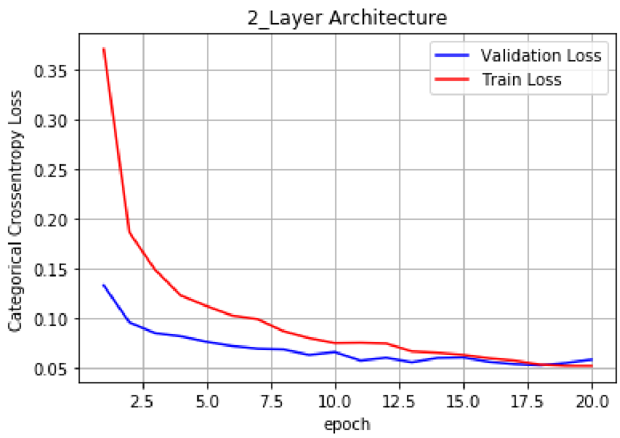
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 10s 161us/step - loss: 0.3707 - acc: 0.8881 - val_l
oss: 0.1326 - val_acc: 0.9559
Epoch 2/20
60000/60000 [==============================] - 5s 83us/step - loss: 0.1860 - acc: 0.9433 -
val_loss: 0.0953 - val_acc: 0.9687
Epoch 3/20
60000/60000 [==============================] - 5s 85us/step - loss: 0.1483 - acc: 0.9549 -
val_loss: 0.0845 - val_acc: 0.9733
Epoch 4/20
60000/60000 [==============================] - 5s 88us/step - loss: 0.1225 - acc: 0.9614 -
val_loss: 0.0813 - val_acc: 0.9743
Epoch 5/20
60000/60000 [==============================] - 5s 86us/step - loss: 0.1119 - acc: 0.9662 -
val_loss: 0.0758 - val_acc: 0.9763
Epoch 6/20
60000/60000 [==============================] - 5s 84us/step - loss: 0.1022 - acc: 0.9678 -
val_loss: 0.0715 - val_acc: 0.9784
Epoch 7/20
60000/60000 [==============================] - 5s 83us/step - loss: 0.0985 - acc: 0.9691 -
val_loss: 0.0688 - val_acc: 0.9788
Epoch 8/20
60000/60000 [==============================] - 5s 82us/step - loss: 0.0864 - acc: 0.9733 -
val_loss: 0.0681 - val_acc: 0.9793
Epoch 9/20
60000/60000 [==============================] - 5s 83us/step - loss: 0.0794 - acc: 0.9751 -
val_loss: 0.0626 - val_acc: 0.9798
Epoch 10/20
60000/60000 [==============================] - 5s 83us/step - loss: 0.0744 - acc: 0.9760 -
val_loss: 0.0655 - val_acc: 0.9796
Epoch 11/20
60000/60000 [==============================] - 5s 86us/step - loss: 0.0748 - acc: 0.9761 -
val_loss: 0.0568 - val_acc: 0.9829
Epoch 12/20
60000/60000 [==============================] - 5s 85us/step - loss: 0.0740 - acc: 0.9764 -
val_loss: 0.0597 - val_acc: 0.9822
Epoch 13/20
60000/60000 [==============================] - 5s 84us/step - loss: 0.0662 - acc: 0.9786 -
val_loss: 0.0552 - val_acc: 0.9833
Epoch 14/20
60000/60000 [==============================] - 5s 84us/step - loss: 0.0647 - acc: 0.9799 -
val_loss: 0.0595 - val_acc: 0.9819
Epoch 15/20
60000/60000 [==============================] - 5s 82us/step - loss: 0.0627 - acc: 0.9805 -
val_loss: 0.0600 - val_acc: 0.9824
Epoch 16/20
60000/60000 [==============================] - 5s 84us/step - loss: 0.0592 - acc: 0.9810 -
val_loss: 0.0556 - val_acc: 0.9835
Epoch 17/20
60000/60000 [==============================] - 5s 85us/step - loss: 0.0568 - acc: 0.9817 -
val_loss: 0.0533 - val_acc: 0.9846
Epoch 18/20
```

```
60000/60000 [==============================] - 5s 84us/step - loss: 0.0529 - acc: 0.9826 -
val_loss: 0.0521 - val_acc: 0.9839
Epoch 19/20
60000/60000 [==============================] - 5s 84us/step - loss: 0.0515 - acc: 0.9829 -
val_loss: 0.0545 - val_acc: 0.9835
Epoch 20/20
60000/60000 [==============================] - 5s 83us/step - loss: 0.0514 - acc: 0.9833 -
val_loss: 0.0579 - val_acc: 0.9837
```

In [15]:

```
score_1 = model_relu.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score_1[0])
print('Test accuracy:', score_1[1])

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

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

vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
plt.title('2_Layer Architecture')
plt.show()
```

```
Test score: 0.057854038857636625
Test accuracy: 0.9837
```

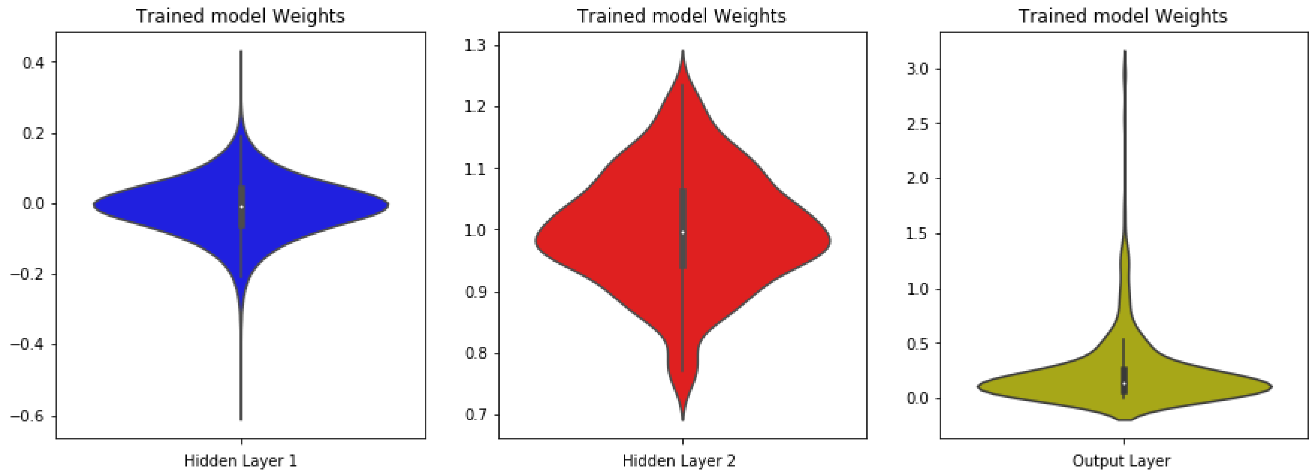


if we observe that above plot after 20 epochs our test loss may grater than our train loss

In [16]:

```
w_after = model_relu.get_weights()

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


fig = plt.figure(figsize=(15,5))
plt.title("Weight matrices after model trained")
plt.subplot(1, 3, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

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

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

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



2 Layer architecture With-out Batch Normalization and Dropout

In [17]:

```
model_relu = Sequential()
#layer-1
model_relu.add(Dense(500, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNor
mal(mean=0.0, stddev=0.039, seed=None)))
#adding batch normalization
#model_relu.add(BatchNormalization())
#addding dropout rate
#model_relu.add(Dropout(0.5))
#layer-2
model_relu.add(Dense(200, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.039
, seed=None)))
#adding batch noramalization
#model_relu.add(BatchNormalization())
#adding drop out rate
#model_relu.add(Dropout(0.5))

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


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

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

#----------------------------------------------------------------------------------------------------
------------------------------

#----------------------------------------------------------------------------------------------------
-------------------------------
```

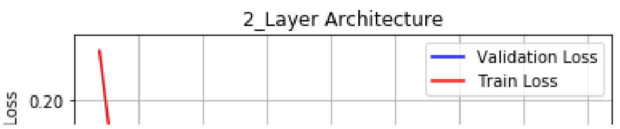
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.2367 - acc: 0.9311 -
val_loss: 0.1117 - val_acc: 0.9632
Epoch 2/20
60000/60000 [==============================] - 3s 48us/step - loss: 0.0851 - acc: 0.9739 -
val_loss: 0.0759 - val_acc: 0.9746
Epoch 3/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.0554 - acc: 0.9825 -
val_loss: 0.0754 - val_acc: 0.9761
Epoch 4/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.0381 - acc: 0.9881 -
val_loss: 0.0682 - val_acc: 0.9796
Epoch 5/20
```

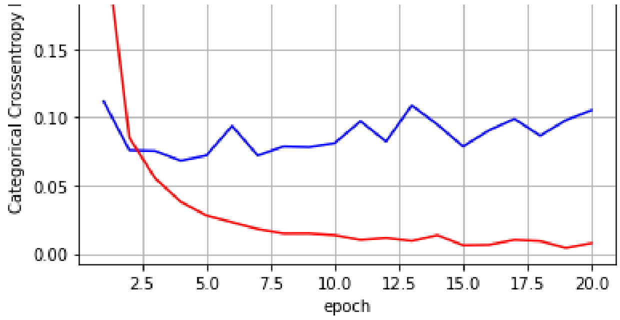
```
60000/60000 [==============================] - 3s 51us/step - loss: 0.0280 - acc: 0.9909 -
val_loss: 0.0721 - val_acc: 0.9782
Epoch 6/20
60000/60000 [==============================] - 3s 49us/step - loss: 0.0230 - acc: 0.9921 -
val_loss: 0.0938 - val_acc: 0.9736
Epoch 7/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.0181 - acc: 0.9942 -
val_loss: 0.0721 - val_acc: 0.9804
Epoch 8/20
60000/60000 [==============================] - 3s 51us/step - loss: 0.0148 - acc: 0.9950 -
val_loss: 0.0787 - val_acc: 0.9798
Epoch 9/20
60000/60000 [==============================] - 3s 49us/step - loss: 0.0149 - acc: 0.9950 -
val_loss: 0.0782 - val_acc: 0.9790
Epoch 10/20
60000/60000 [==============================] - 3s 49us/step - loss: 0.0136 - acc: 0.9956 -
val_loss: 0.0811 - val_acc: 0.9803
Epoch 11/20
60000/60000 [==============================] - 3s 49us/step - loss: 0.0102 - acc: 0.9968 -
val_loss: 0.0973 - val_acc: 0.9763
Epoch 12/20
60000/60000 [==============================] - 3s 49us/step - loss: 0.0116 - acc: 0.9962 -
val_loss: 0.0824 - val_acc: 0.9792
Epoch 13/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.0094 - acc: 0.9970 -
val_loss: 0.1089 - val_acc: 0.9755
Epoch 14/20
60000/60000 [==============================] - 3s 49us/step - loss: 0.0136 - acc: 0.9956 -
val_loss: 0.0948 - val_acc: 0.9756
Epoch 15/20
60000/60000 [==============================] - 3s 52us/step - loss: 0.0062 - acc: 0.9980 -
val_loss: 0.0787 - val_acc: 0.9816
Epoch 16/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.0065 - acc: 0.9979 -
val_loss: 0.0905 - val_acc: 0.9798
Epoch 17/20
60000/60000 [==============================] - 3s 49us/step - loss: 0.0102 - acc: 0.9965 -
val_loss: 0.0990 - val_acc: 0.9795
Epoch 18/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.0093 - acc: 0.9971 -
val_loss: 0.0867 - val_acc: 0.9800
Epoch 19/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.0042 - acc: 0.9987 -
val_loss: 0.0980 - val_acc: 0.9801
Epoch 20/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.0077 - acc: 0.9974 -
val_loss: 0.1053 - val_acc: 0.9792
```

In [18]:

```
score_1 = model_relu.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score_1[0])
print('Test accuracy:', score_1[1])

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

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

vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
plt.title('2_Layer Architecture')
plt.show()
```

```
Test score: 0.10529097638992689
Test accuracy: 0.9792
```

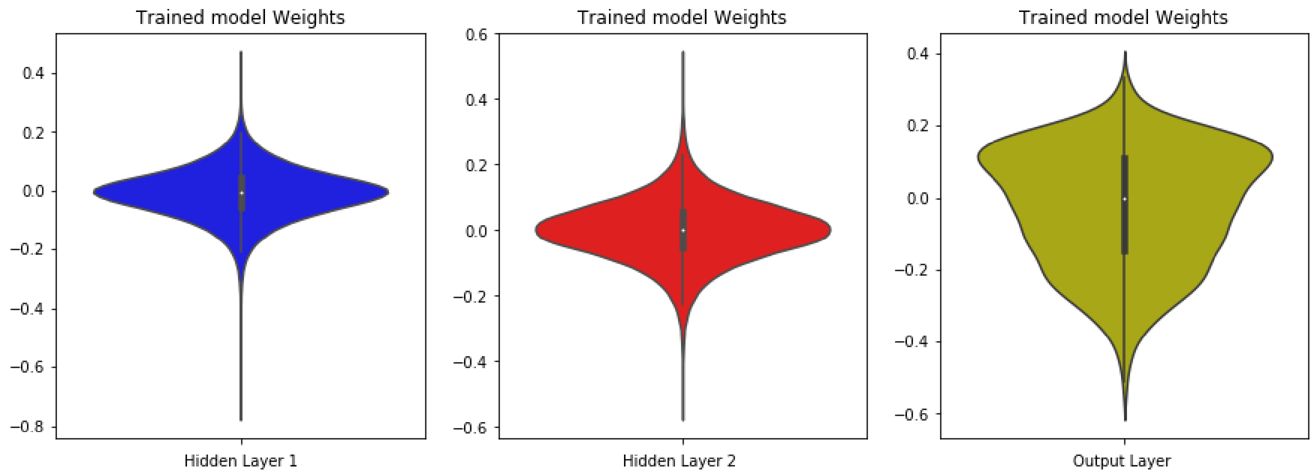




Here we see that in above plot with out apply of batch-normalization and drop out we got test loss > train loss

In [19]:

```
w_after = model_relu.get_weights()

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


fig = plt.figure(figsize=(15,5))
plt.title("Weight matrices after model trained")
plt.subplot(1, 3, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

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

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



2 layer architecture We also experiment with Different optimizer like Adadelta with different drop-out rate 0.2

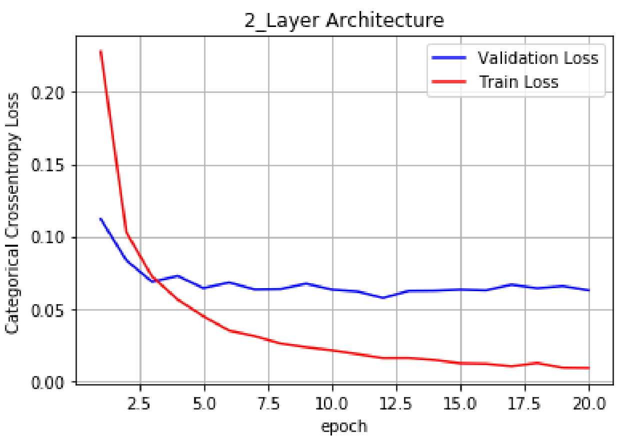
In [20]:

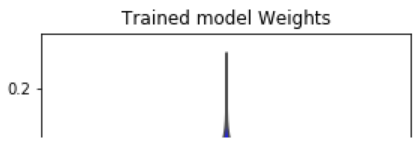
```
model_relu = Sequential()
#layer-1
model_relu.add(Dense(500, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNor
mal(mean=0.0, stddev=0.039, seed=None)))
#adding batch normalization
```

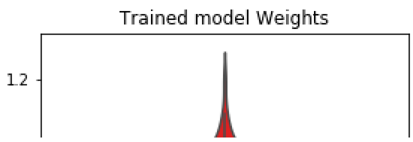
```
model_relu.add(BatchNormalization())
#addding dropout rate
model_relu.add(Dropout(0.2))
#layer-2
model_relu.add(Dense(200, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.039
, seed=None)))
#adding batch noramalization
model_relu.add(BatchNormalization())
#adding drop out rate
model_relu.add(Dropout(0.2))

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


#print(model_relu.summary())
#using optimizer Adadelta
model_relu.compile(optimizer='Adadelta', loss='categorical_crossentropy', metrics=['accuracy'])

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

#------------------------------------------------train and test error plots -----------------------
------------------------------------------------------------
score_1 = model_relu.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score_1[0])
print('Test accuracy:', score_1[1])

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

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

vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
plt.title('2_Layer Architecture')
plt.show()
#-------------------------------------------------------------layer wise plots --------------------
--------------------------------------------------
w_after = model_relu.get_weights()

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


fig = plt.figure(figsize=(15,5))
plt.title("Weight matrices after model trained")
plt.subplot(1, 3, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

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

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

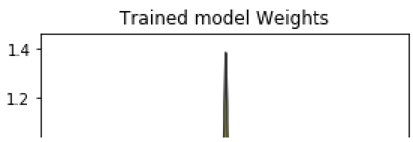
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 6s 100us/step - loss: 0.2279 - acc: 0.9306 -
val_loss: 0.1119 - val_acc: 0.9662
Epoch 2/20
60000/60000 [==============================] - 5s 89us/step - loss: 0.1027 - acc: 0.9680 -
val_loss: 0.0833 - val_acc: 0.9751
Epoch 3/20
60000/60000 [==============================] - 5s 88us/step - loss: 0.0721 - acc: 0.9778 -
val_loss: 0.0684 - val_acc: 0.9789
Epoch 4/20
```

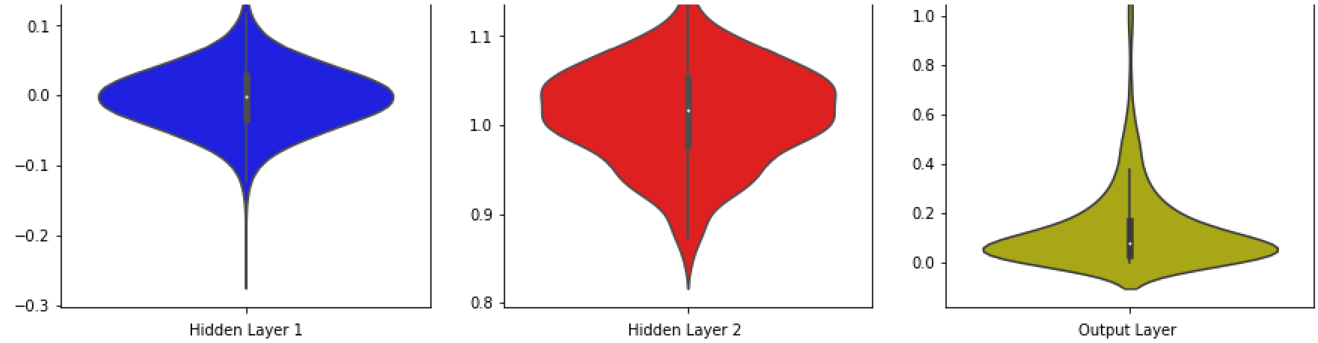
```
Epoch 4/20
60000/60000 [==============================] - 5s 87us/step - loss: 0.0562 - acc: 0.9823 -
val_loss: 0.0725 - val_acc: 0.9772
Epoch 5/20
60000/60000 [==============================] - 5s 87us/step - loss: 0.0446 - acc: 0.9862 -
val_loss: 0.0641 - val_acc: 0.9812
Epoch 6/20
60000/60000 [==============================] - 5s 87us/step - loss: 0.0347 - acc: 0.9889 -
val_loss: 0.0680 - val_acc: 0.9810
Epoch 7/20
60000/60000 [==============================] - 5s 89us/step - loss: 0.0308 - acc: 0.9898 -
val_loss: 0.0631 - val_acc: 0.9812
Epoch 8/20
60000/60000 [==============================] - 5s 88us/step - loss: 0.0258 - acc: 0.9916 -
val_loss: 0.0634 - val_acc: 0.9822
Epoch 9/20
60000/60000 [==============================] - 5s 88us/step - loss: 0.0231 - acc: 0.9921 -
val_loss: 0.0672 - val_acc: 0.9817
Epoch 10/20
60000/60000 [==============================] - 5s 88us/step - loss: 0.0210 - acc: 0.9932 -
val_loss: 0.0631 - val_acc: 0.9840
Epoch 11/20
60000/60000 [==============================] - 5s 89us/step - loss: 0.0184 - acc: 0.9939 -
val_loss: 0.0618 - val_acc: 0.9833
Epoch 12/20
60000/60000 [==============================] - 5s 88us/step - loss: 0.0157 - acc: 0.9949 -
val_loss: 0.0573 - val_acc: 0.9846
Epoch 13/20
60000/60000 [==============================] - 5s 88us/step - loss: 0.0157 - acc: 0.9950 -
val_loss: 0.0622 - val_acc: 0.9836
Epoch 14/20
60000/60000 [==============================] - 5s 87us/step - loss: 0.0144 - acc: 0.9953 -
val_loss: 0.0623 - val_acc: 0.9850
Epoch 15/20
60000/60000 [==============================] - 5s 88us/step - loss: 0.0120 - acc: 0.9961 -
val_loss: 0.0630 - val_acc: 0.9833
Epoch 16/20
60000/60000 [==============================] - 5s 88us/step - loss: 0.0117 - acc: 0.9963 -
val_loss: 0.0625 - val_acc: 0.9852
Epoch 17/20
60000/60000 [==============================] - 5s 87us/step - loss: 0.0100 - acc: 0.9966 -
val_loss: 0.0665 - val_acc: 0.9843
Epoch 18/20
60000/60000 [==============================] - 5s 89us/step - loss: 0.0123 - acc: 0.9960 -
val_loss: 0.0640 - val_acc: 0.9849
Epoch 19/20
60000/60000 [==============================] - 5s 88us/step - loss: 0.0089 - acc: 0.9972 -
val_loss: 0.0655 - val_acc: 0.9861
Epoch 20/20
60000/60000 [==============================] - 5s 89us/step - loss: 0.0088 - acc: 0.9972 -
val_loss: 0.0626 - val_acc: 0.9858
Test score: 0.06257566632076009
Test accuracy: 0.9858
```











Above We got our test-loss > train-loss which is not a good performance

2 layer architecture We also experiment with by Adding only one batch normalization and one drop-out after first layer with adam with drop 5.0

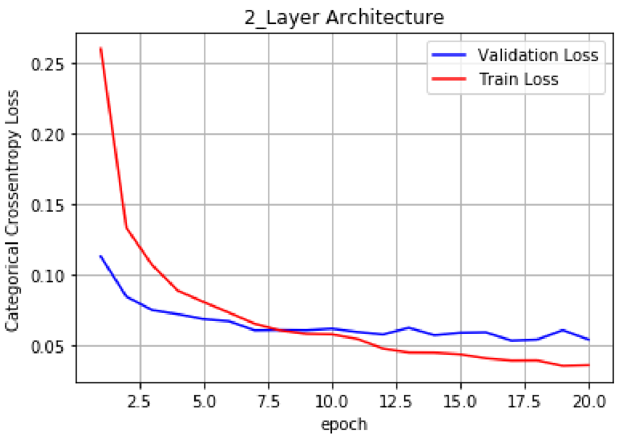
In [21]:

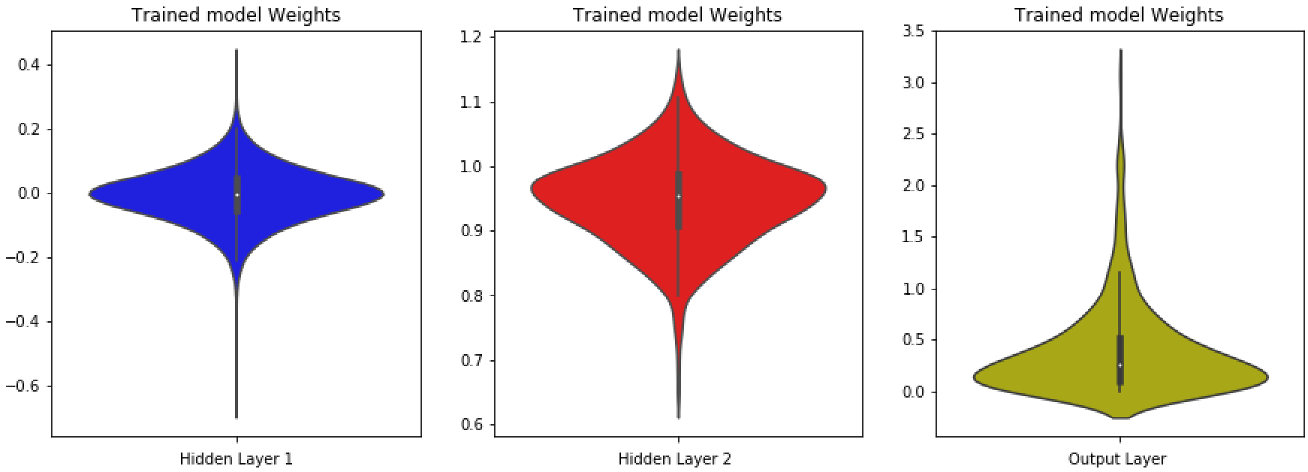
```
model_relu = Sequential()
#layer-1
model_relu.add(Dense(500, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNor
mal(mean=0.0, stddev=0.039, seed=None)))
#adding batch normalization
model_relu.add(BatchNormalization())
#addding dropout rate
model_relu.add(Dropout(0.5))
#layer-2
model_relu.add(Dense(200, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.039
, seed=None)))
#adding batch noramalization
#model_relu.add(BatchNormalization())
#adding drop out rate
#model_relu.add(Dropout(0.2))

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


#print(model_relu.summary())
#using optimizer Adadelta
model_relu.compile(optimizer='Adam', loss='categorical_crossentropy', metrics=['accuracy'])

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

#-------------------------------------------------train and test error plots ----------------------
------------------------------------------------------------
score_1 = model_relu.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score_1[0])
print('Test accuracy:', score_1[1])

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

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

vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
plt.title('2_Layer Architecture')
plt.show()
#--------------------------------------------------------------layer wise plots ------------------
--------------------------------------------------
w_after = model_relu.get_weights()

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

```
fig = plt.figure(figsize=(15,5))
plt.title("Weight matrices after model trained")
plt.subplot(1, 3, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

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

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

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 5s 81us/step - loss: 0.2600 - acc: 0.9211 -
val_loss: 0.1131 - val_acc: 0.9642
Epoch 2/20
60000/60000 [==============================] - 4s 69us/step - loss: 0.1335 - acc: 0.9582 -
val_loss: 0.0849 - val_acc: 0.9737
Epoch 3/20
60000/60000 [==============================] - 4s 67us/step - loss: 0.1072 - acc: 0.9666 -
val_loss: 0.0754 - val_acc: 0.9752
Epoch 4/20
60000/60000 [==============================] - 4s 70us/step - loss: 0.0891 - acc: 0.9716 -
val_loss: 0.0724 - val_acc: 0.9783
Epoch 5/20
60000/60000 [==============================] - 4s 70us/step - loss: 0.0811 - acc: 0.9739 -
val_loss: 0.0690 - val_acc: 0.9789
Epoch 6/20
60000/60000 [==============================] - 4s 70us/step - loss: 0.0735 - acc: 0.9766 -
val_loss: 0.0674 - val_acc: 0.9805
Epoch 7/20
60000/60000 [==============================] - 4s 67us/step - loss: 0.0656 - acc: 0.9784 -
val_loss: 0.0610 - val_acc: 0.9827
Epoch 8/20
60000/60000 [==============================] - 4s 68us/step - loss: 0.0609 - acc: 0.9807 -
val_loss: 0.0612 - val_acc: 0.9807
Epoch 9/20
60000/60000 [==============================] - 4s 68us/step - loss: 0.0585 - acc: 0.9800 -
val_loss: 0.0610 - val_acc: 0.9816
Epoch 10/20
60000/60000 [==============================] - 4s 67us/step - loss: 0.0582 - acc: 0.9812 -
val_loss: 0.0622 - val_acc: 0.9816
Epoch 11/20
60000/60000 [==============================] - 4s 71us/step - loss: 0.0549 - acc: 0.9818 -
val_loss: 0.0598 - val_acc: 0.9830
Epoch 12/20
60000/60000 [==============================] - 4s 68us/step - loss: 0.0481 - acc: 0.9842 -
val_loss: 0.0581 - val_acc: 0.9833
Epoch 13/20
60000/60000 [==============================] - 4s 67us/step - loss: 0.0453 - acc: 0.9847 -
val_loss: 0.0628 - val_acc: 0.9834
Epoch 14/20
60000/60000 [==============================] - 4s 67us/step - loss: 0.0452 - acc: 0.9851 -
val_loss: 0.0575 - val_acc: 0.9838
Epoch 15/20
60000/60000 [==============================] - 4s 68us/step - loss: 0.0441 - acc: 0.9853 -
val_loss: 0.0593 - val_acc: 0.9842
Epoch 16/20
60000/60000 [==============================] - 4s 68us/step - loss: 0.0412 - acc: 0.9865 -
val_loss: 0.0595 - val_acc: 0.9836
Epoch 17/20
60000/60000 [==============================] - 4s 68us/step - loss: 0.0396 - acc: 0.9870 -
val_loss: 0.0537 - val_acc: 0.9842
Epoch 18/20
60000/60000 [==============================] - 4s 67us/step - loss: 0.0397 - acc: 0.9873 -
val_loss: 0.0545 - val_acc: 0.9852
Epoch 19/20
60000/60000 [==============================] - 4s 67us/step - loss: 0.0359 - acc: 0.9881 -
val_loss: 0.0611 - val_acc: 0.9837
```

```
Epoch 20/20
60000/60000 [==============================] - 4s 67us/step - loss: 0.0364 - acc: 0.9881 -
val_loss: 0.0545 - val_acc: 0.9852
Test score: 0.054469384077978064
Test accuracy: 0.9852
```





Above We got our test-loss > train-loss which is not a good performance

2 layer architecture We also experiment with by Adding only one batch normalization and one-drop-out before last layer with Adam with drop 0.5

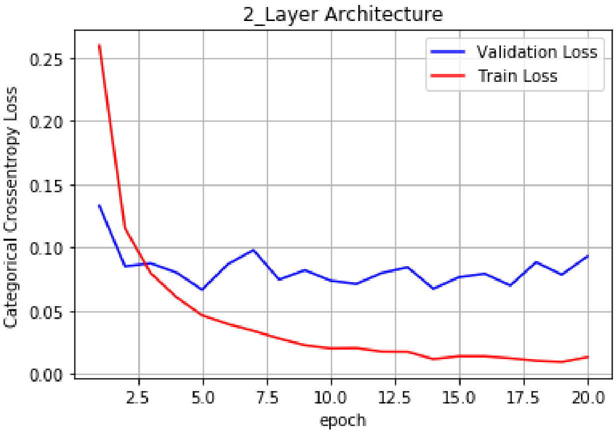
In [22]:

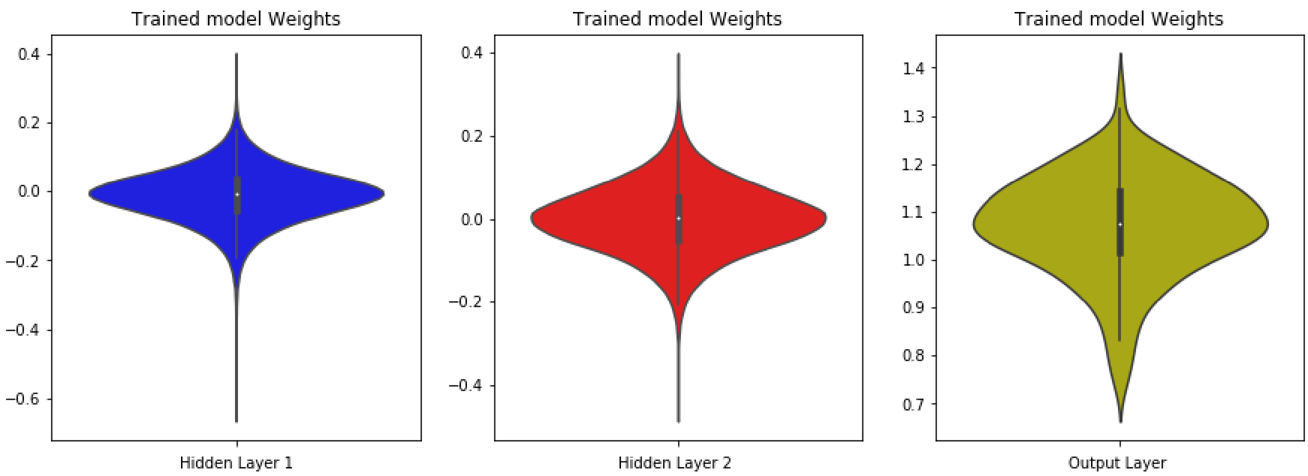
```
model_relu = Sequential()
#layer-1
model_relu.add(Dense(500, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNor
mal(mean=0.0, stddev=0.039, seed=None)))
#adding batch normalization
#model_relu.add(BatchNormalization())
#addding dropout rate
#model_relu.add(Dropout(0.2))
#layer-2
model_relu.add(Dense(200, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.039
, seed=None)))
#adding batch noramalization
model_relu.add(BatchNormalization())
#adding drop out rate
model_relu.add(Dropout(0.5))

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


#print(model_relu.summary())
#using optimizer Adadelta
model_relu.compile(optimizer='Adam', loss='categorical_crossentropy', metrics=['accuracy'])
```

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

#---------------------------------------------------train and test error plots ----------------------
------------------------------------------------------------
score_1 = model_relu.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score_1[0])
print('Test accuracy:', score_1[1])

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

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

vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
plt.title('2_Layer Architecture')
plt.show()
#----------------------------------------------------------------layer wise plots -------------------
--------------------------------------------------
w_after = model_relu.get_weights()

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


fig = plt.figure(figsize=(15,5))
plt.title("Weight matrices after model trained")
plt.subplot(1, 3, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

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

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

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 5s 79us/step - loss: 0.2597 - acc: 0.9221 -
val_loss: 0.1330 - val_acc: 0.9586
Epoch 2/20
60000/60000 [==============================] - 4s 66us/step - loss: 0.1153 - acc: 0.9657 -
val_loss: 0.0851 - val_acc: 0.9737
Epoch 3/20
60000/60000 [==============================] - 4s 65us/step - loss: 0.0797 - acc: 0.9758 -
val_loss: 0.0875 - val_acc: 0.9724
Epoch 4/20
60000/60000 [==============================] - 4s 66us/step - loss: 0.0609 - acc: 0.9811 -
val_loss: 0.0803 - val_acc: 0.9730
Epoch 5/20
60000/60000 [==============================] - 4s 65us/step - loss: 0.0465 - acc: 0.9859 -
val_loss: 0.0667 - val_acc: 0.9782
Epoch 6/20
60000/60000 [==============================] - 4s 66us/step - loss: 0.0396 - acc: 0.9871 -
val_loss: 0.0868 - val_acc: 0.9744
Epoch 7/20
60000/60000 [==============================] - 4s 65us/step - loss: 0.0342 - acc: 0.9888 -
val_loss: 0.0980 - val_acc: 0.9724
Epoch 8/20
60000/60000 [==============================] - 4s 65us/step - loss: 0.0280 - acc: 0.9911 -
val_loss: 0.0747 - val_acc: 0.9800
Epoch 9/20
60000/60000 [==============================] - 4s 67us/step - loss: 0.0228 - acc: 0.9925 -
val_loss: 0.0821 - val_acc: 0.9772
```

```
Epoch 10/20
60000/60000 [==============================] - 4s 68us/step - loss: 0.0203 - acc: 0.9935 -
val_loss: 0.0739 - val_acc: 0.9795
Epoch 11/20
60000/60000 [==============================] - 4s 68us/step - loss: 0.0206 - acc: 0.9931 -
val_loss: 0.0712 - val_acc: 0.9805
Epoch 12/20
60000/60000 [==============================] - 4s 69us/step - loss: 0.0178 - acc: 0.9943 -
val_loss: 0.0799 - val_acc: 0.9788
Epoch 13/20
60000/60000 [==============================] - 4s 67us/step - loss: 0.0176 - acc: 0.9943 -
val_loss: 0.0844 - val_acc: 0.9792
Epoch 14/20
60000/60000 [==============================] - 4s 67us/step - loss: 0.0118 - acc: 0.9959 -
val_loss: 0.0674 - val_acc: 0.9819
Epoch 15/20
60000/60000 [==============================] - 4s 65us/step - loss: 0.0141 - acc: 0.9955 -
val_loss: 0.0766 - val_acc: 0.9823
Epoch 16/20
60000/60000 [==============================] - 4s 66us/step - loss: 0.0141 - acc: 0.9952 -
val_loss: 0.0793 - val_acc: 0.9809
Epoch 17/20
60000/60000 [==============================] - 4s 66us/step - loss: 0.0125 - acc: 0.9958 -
val_loss: 0.0700 - val_acc: 0.9840
Epoch 18/20
60000/60000 [==============================] - 4s 66us/step - loss: 0.0105 - acc: 0.9963 -
val_loss: 0.0884 - val_acc: 0.9813
Epoch 19/20
60000/60000 [==============================] - 4s 66us/step - loss: 0.0095 - acc: 0.9965 -
val_loss: 0.0785 - val_acc: 0.9826
Epoch 20/20
60000/60000 [==============================] - 4s 66us/step - loss: 0.0134 - acc: 0.9956 -
val_loss: 0.0930 - val_acc: 0.9800
Test score: 0.09304900475722334
Test accuracy: 0.98
```





Above We got our test-loss > train-loss which is not a good performance

3-layer Architecture with Batch-Normalization and Dropout

In [23]:

```
model_relu2 = Sequential()
#layer-1
model_relu2.add(Dense(500, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNo
rmal(mean=0.0, stddev=0.039, seed=None)))
#adding batch normalization
model_relu2.add(BatchNormalization())
#addding dropout rate
model_relu2.add(Dropout(0.5))
#layer-2
model_relu2.add(Dense(300, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.03
9, seed=None)))
#adding batch noramalization
model_relu2.add(BatchNormalization())
#adding drop out rate
model_relu2.add(Dropout(0.5))
#layer-3
model_relu2.add(Dense(200, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.03
9, seed=None)))
#adding batch noramalization
model_relu2.add(BatchNormalization())
#adding drop out rate
model_relu2.add(Dropout(0.5))

model_relu2.add(Dense(output_dim, activation='softmax'))


#print(model_relu2.summary())
#using optimizer adam
model_relu2.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history = model_relu2.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, vali
dation_data=(X_test, Y_test))
```

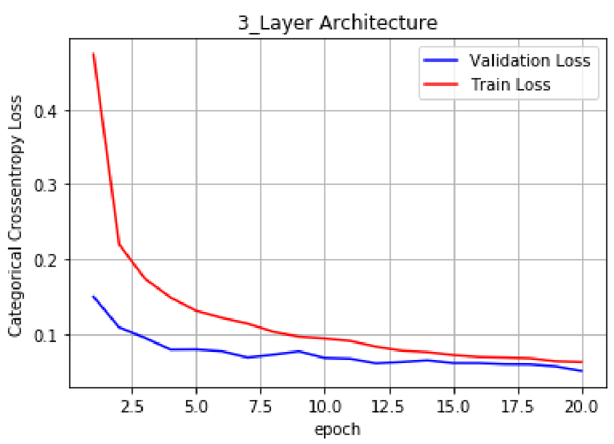
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 8s 133us/step - loss: 0.4738 - acc: 0.8567 -
val_loss: 0.1498 - val_acc: 0.9544
Epoch 2/20
60000/60000 [==============================] - 7s 111us/step - loss: 0.2196 - acc: 0.9350 -
val_loss: 0.1086 - val_acc: 0.9653
Epoch 3/20
60000/60000 [==============================] - 7s 110us/step - loss: 0.1737 - acc: 0.9482 -
val_loss: 0.0947 - val_acc: 0.9693
Epoch 4/20
60000/60000 [==============================] - 7s 112us/step - loss: 0.1487 - acc: 0.9558 -
val_loss: 0.0790 - val_acc: 0.9749
Epoch 5/20
60000/60000 [==============================] - 7s 111us/step - loss: 0.1309 - acc: 0.9608 -
val_loss: 0.0792 - val_acc: 0.9744
Epoch 6/20
60000/60000 [==============================] - 7s 111us/step - loss: 0.1215 - acc: 0.9637 -
val_loss: 0.0767 - val_acc: 0.9777
Epoch 7/20
60000/60000 [==============================] - 7s 111us/step - loss: 0.1137 - acc: 0.9668 -
val_loss: 0.0684 - val_acc: 0.9791
Epoch 8/20
60000/60000 [==============================] - 7s 111us/step - loss: 0.1028 - acc: 0.9692 -
val_loss: 0.0722 - val_acc: 0.9783
Epoch 9/20
60000/60000 [==============================] - 7s 110us/step - loss: 0.0962 - acc: 0.9699 -
val_loss: 0.0766 - val_acc: 0.9764
Epoch 10/20
60000/60000 [==============================] - 7s 111us/step - loss: 0.0939 - acc: 0.9711 -
val_loss: 0.0678 - val_acc: 0.9792
Epoch 11/20
60000/60000 [==============================] - 7s 110us/step - loss: 0.0906 - acc: 0.9722 -
val_loss: 0.0668 - val_acc: 0.9801
Epoch 12/20
60000/60000 [==============================] - 7s 110us/step - loss: 0.0828 - acc: 0.9747 -
val_loss: 0.0606 - val_acc: 0.9809
Epoch 13/20
```

```
60000/60000 [==============================] - 7s 111us/step - loss: 0.0775 - acc: 0.9758 -
val_loss: 0.0624 - val_acc: 0.9813
Epoch 14/20
60000/60000 [==============================] - 7s 111us/step - loss: 0.0755 - acc: 0.9765 -
val_loss: 0.0647 - val_acc: 0.9804
Epoch 15/20
60000/60000 [==============================] - 7s 110us/step - loss: 0.0717 - acc: 0.9780 -
val_loss: 0.0610 - val_acc: 0.9822
Epoch 16/20
60000/60000 [==============================] - 7s 109us/step - loss: 0.0692 - acc: 0.9786 -
val_loss: 0.0609 - val_acc: 0.9814
Epoch 17/20
60000/60000 [==============================] - 7s 111us/step - loss: 0.0683 - acc: 0.9785 -
val_loss: 0.0595 - val_acc: 0.9834
Epoch 18/20
60000/60000 [==============================] - 7s 112us/step - loss: 0.0673 - acc: 0.9789 -
val_loss: 0.0592 - val_acc: 0.9824
Epoch 19/20
60000/60000 [==============================] - 7s 113us/step - loss: 0.0634 - acc: 0.9798 -
val_loss: 0.0565 - val_acc: 0.9837
Epoch 20/20
60000/60000 [==============================] - 7s 110us/step - loss: 0.0623 - acc: 0.9806 -
val_loss: 0.0504 - val_acc: 0.9849
```

In [24]:

```
score_4 = model_relu2.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score_4[0])
print('Test accuracy:', score_4[1])

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

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

vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
plt.title('3_Layer Architecture')
plt.show()
```

```
Test score: 0.0504366103822249
Test accuracy: 0.9849
```

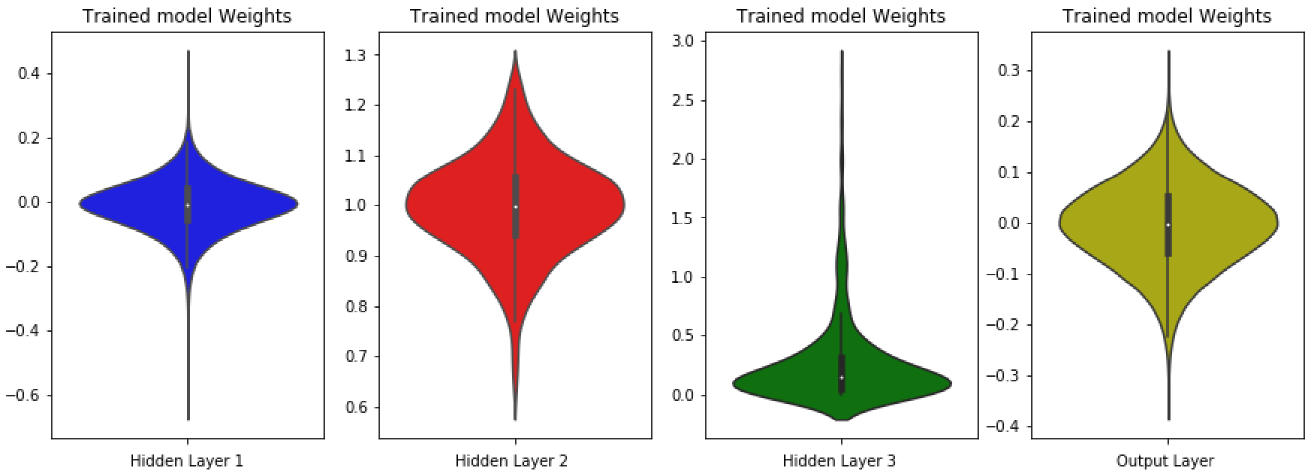


In above plot at epoch 20 our train and test loss becomes same

In [25]:

```
w_after = model_relu2.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(figsize=(15,5))
plt.title("Weight matrices after model trained")
plt.subplot(1, 4, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

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

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


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



3-layer Architecture with-out Batch-Normalization and Dropout

In [26]:

```
model_relu2 = Sequential()
#layer-1
model_relu2.add(Dense(500, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNo
rmal(mean=0.0, stddev=0.039, seed=None)))
#adding batch normalization
#model_relu2.add(BatchNormalization())
#addding dropout rate
#model_relu2.add(Dropout(0.5))
#layer-2
model_relu2.add(Dense(300, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.03
9, seed=None)))
#adding batch noramalization
#model_relu2.add(BatchNormalization())
#adding drop out rate
#model_relu2.add(Dropout(0.5))
#layer-3
model_relu2.add(Dense(200, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.03
9, seed=None)))
#adding batch noramalization
#model_relu2.add(BatchNormalization())
#adding drop out rate
#model_relu2.add(Dropout(0.5))
```

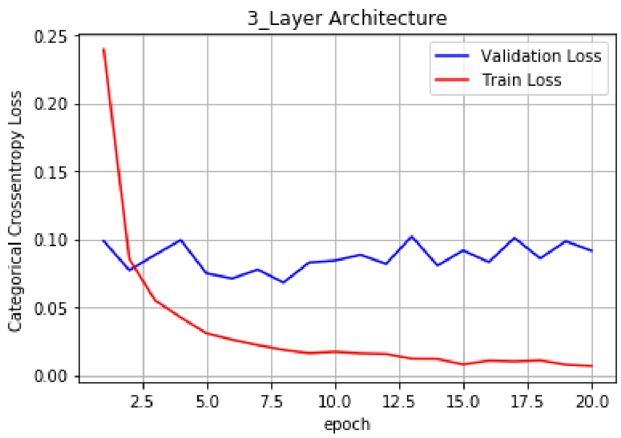
```python
model_relu2.add(Dense(output_dim, activation='softmax'))


#print(model_relu2.summary())
#using optimizer adam
model_relu2.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history = model_relu2.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, vali
dation_data=(X_test, Y_test))

#----------------------------------------------------------------------------------------------------
---------------------------------------
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 4s 73us/step - loss: 0.2393 - acc: 0.9295 -
val_loss: 0.0985 - val_acc: 0.9686
Epoch 2/20
60000/60000 [==============================] - 4s 59us/step - loss: 0.0852 - acc: 0.9740 -
val_loss: 0.0770 - val_acc: 0.9754
Epoch 3/20
60000/60000 [==============================] - 4s 59us/step - loss: 0.0549 - acc: 0.9824 -
val_loss: 0.0884 - val_acc: 0.9741
Epoch 4/20
60000/60000 [==============================] - 4s 60us/step - loss: 0.0423 - acc: 0.9867 -
val_loss: 0.0993 - val_acc: 0.9702
Epoch 5/20
60000/60000 [==============================] - 4s 62us/step - loss: 0.0307 - acc: 0.9899 -
val_loss: 0.0748 - val_acc: 0.9799
Epoch 6/20
60000/60000 [==============================] - 4s 61us/step - loss: 0.0259 - acc: 0.9916 -
val_loss: 0.0709 - val_acc: 0.9806
Epoch 7/20
60000/60000 [==============================] - 4s 59us/step - loss: 0.0220 - acc: 0.9931 -
val_loss: 0.0775 - val_acc: 0.9802
Epoch 8/20
60000/60000 [==============================] - 4s 60us/step - loss: 0.0185 - acc: 0.9936 -
val_loss: 0.0680 - val_acc: 0.9813
Epoch 9/20
60000/60000 [==============================] - 3s 58us/step - loss: 0.0161 - acc: 0.9948 -
val_loss: 0.0827 - val_acc: 0.9786
Epoch 10/20
60000/60000 [==============================] - 4s 59us/step - loss: 0.0171 - acc: 0.9946 -
val_loss: 0.0841 - val_acc: 0.9794
Epoch 11/20
60000/60000 [==============================] - 4s 61us/step - loss: 0.0160 - acc: 0.9946 -
val_loss: 0.0884 - val_acc: 0.9795
Epoch 12/20
60000/60000 [==============================] - 4s 60us/step - loss: 0.0155 - acc: 0.9950 -
val_loss: 0.0817 - val_acc: 0.9802
Epoch 13/20
60000/60000 [==============================] - 3s 58us/step - loss: 0.0120 - acc: 0.9960 -
val_loss: 0.1019 - val_acc: 0.9762
Epoch 14/20
60000/60000 [==============================] - 4s 59us/step - loss: 0.0118 - acc: 0.9962 -
val_loss: 0.0805 - val_acc: 0.9827
Epoch 15/20
60000/60000 [==============================] - 4s 59us/step - loss: 0.0079 - acc: 0.9975 -
val_loss: 0.0916 - val_acc: 0.9817
Epoch 16/20
60000/60000 [==============================] - 4s 58us/step - loss: 0.0106 - acc: 0.9964 -
val_loss: 0.0830 - val_acc: 0.9827
Epoch 17/20
60000/60000 [==============================] - 4s 59us/step - loss: 0.0100 - acc: 0.9966 -
val_loss: 0.1009 - val_acc: 0.9799
Epoch 18/20
60000/60000 [==============================] - 4s 59us/step - loss: 0.0108 - acc: 0.9968 -
val_loss: 0.0858 - val_acc: 0.9812
Epoch 19/20
60000/60000 [==============================] - 3s 58us/step - loss: 0.0077 - acc: 0.9977 -
val_loss: 0.0984 - val_acc: 0.9818
Epoch 20/20
60000/60000 [==============================] - 3s 58us/step - loss: 0.0066 - acc: 0.9980 -
val_loss: 0.0914 - val_acc: 0.9813
```

In [27]:

```
score_4 = model_relu2.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score_4[0])
print('Test accuracy:', score_4[1])

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

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

vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
plt.title('3_Layer Architecture')
plt.show()
```

```
Test score: 0.09140819830668388
Test accuracy: 0.9813
```

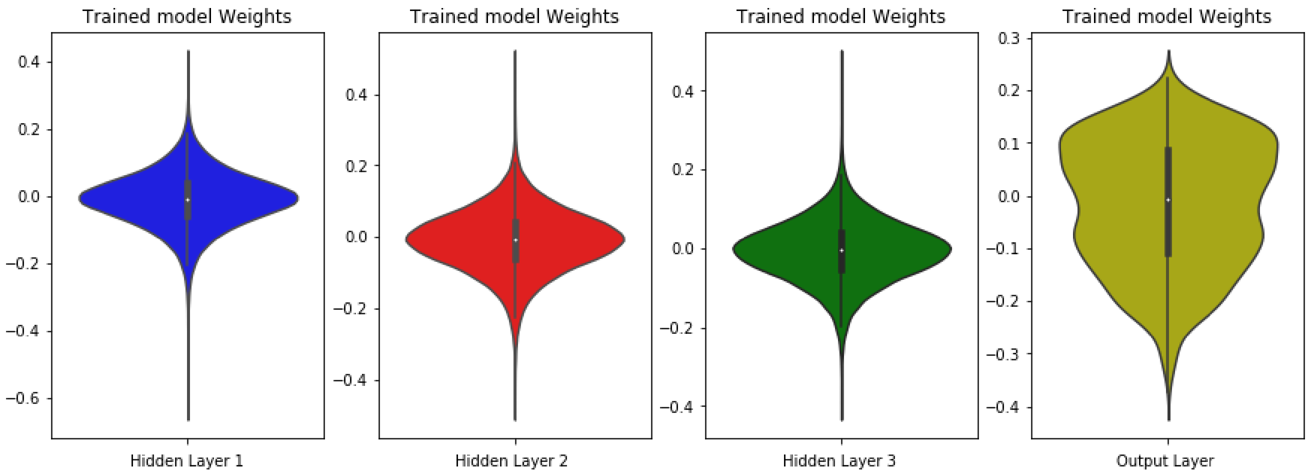


Here we see that in above plot with out apply of batch-normalization and drop out we got test loss > train loss

In [28]:

```
w_after = model_relu2.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(figsize=(15,5))
plt.title("Weight matrices after model trained")

plt.subplot(1, 4, 1)

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

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

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


plt.subplot(1, 4, 4)
plt.title("Trained model Weights")
```

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



3 layer architecture We also experiment with Different optimizer like Adadelta with different drop-out rate 0.2

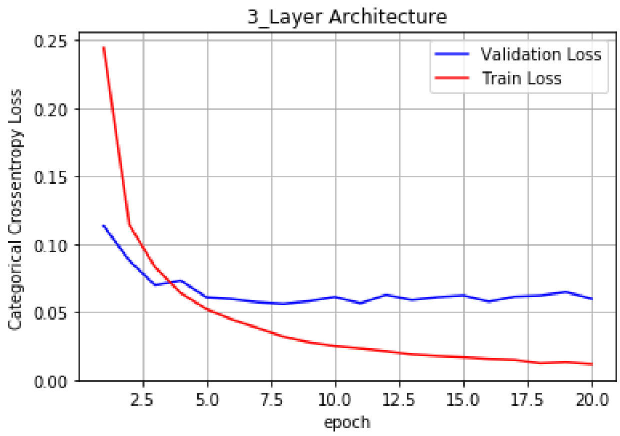
In [29]:

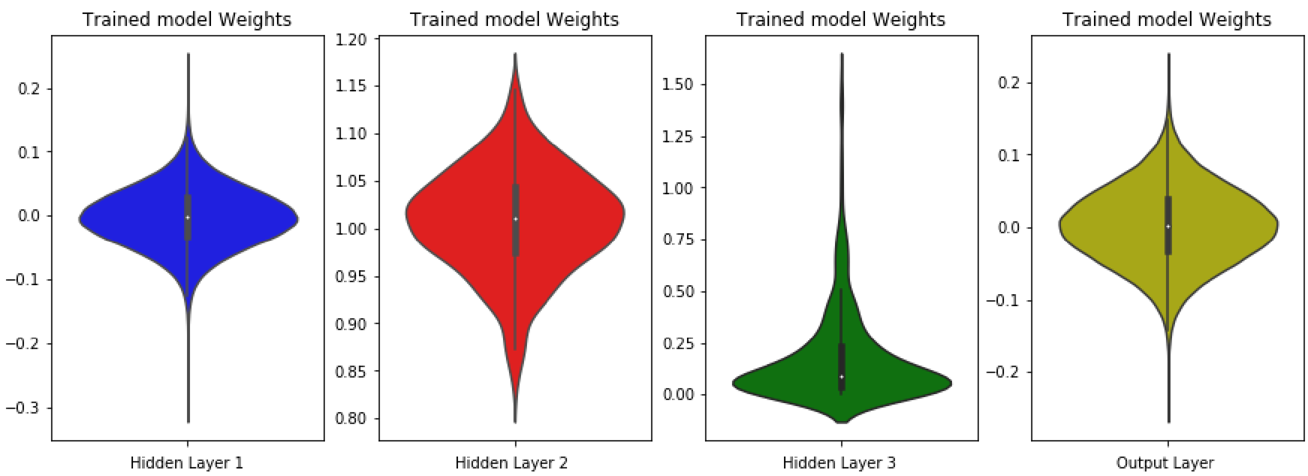
```
model_relu2 = Sequential()
#layer-1
model_relu2.add(Dense(500, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNo
rmal(mean=0.0, stddev=0.039, seed=None)))
#adding batch normalization
model_relu2.add(BatchNormalization())
#addding dropout rate
model_relu2.add(Dropout(0.2))
#layer-2
model_relu2.add(Dense(300, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.03
9, seed=None)))
#adding batch noramalization
model_relu2.add(BatchNormalization())
#adding drop out rate
model_relu2.add(Dropout(0.2))
#layer-3
model_relu2.add(Dense(200, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.03
9, seed=None)))
#adding batch noramalization
model_relu2.add(BatchNormalization())
#adding drop out rate
model_relu2.add(Dropout(0.2))

model_relu2.add(Dense(output_dim, activation='softmax'))


#print(model_relu2.summary())
#using optimizer adam
model_relu2.compile(optimizer='Adadelta', loss='categorical_crossentropy', metrics=['accuracy'])

history = model_relu2.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, vali
dation_data=(X_test, Y_test))

#---------------------------------------------------------------train and test error ---------------
-------------------------------------------------------------

score_4 = model_relu2.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score_4[0])
print('Test accuracy:', score_4[1])

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

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

```
vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
plt.title('3_Layer Architecture')
plt.show()

#------------------------------------------------------------------layers performance -----------
---------------------------------------------------
w_after = model_relu2.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(figsize=(15,5))
plt.title("Weight matrices after model trained")

plt.subplot(1, 4, 1)

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

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

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


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

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 9s 145us/step - loss: 0.2440 - acc: 0.9250 -
val_loss: 0.1133 - val_acc: 0.9648
Epoch 2/20
60000/60000 [==============================] - 7s 116us/step - loss: 0.1140 - acc: 0.9655 -
val_loss: 0.0878 - val_acc: 0.9710
Epoch 3/20
60000/60000 [==============================] - 7s 116us/step - loss: 0.0830 - acc: 0.9738 -
val_loss: 0.0698 - val_acc: 0.9782
Epoch 4/20
60000/60000 [==============================] - 7s 118us/step - loss: 0.0640 - acc: 0.9796 -
val_loss: 0.0732 - val_acc: 0.9783
Epoch 5/20
60000/60000 [==============================] - 7s 118us/step - loss: 0.0522 - acc: 0.9837 -
val_loss: 0.0609 - val_acc: 0.9811
Epoch 6/20
60000/60000 [==============================] - 7s 119us/step - loss: 0.0445 - acc: 0.9853 -
val_loss: 0.0596 - val_acc: 0.9819
Epoch 7/20
60000/60000 [==============================] - 7s 116us/step - loss: 0.0383 - acc: 0.9873 -
val_loss: 0.0573 - val_acc: 0.9835
Epoch 8/20
60000/60000 [==============================] - 7s 117us/step - loss: 0.0320 - acc: 0.9897 -
val_loss: 0.0560 - val_acc: 0.9834
Epoch 9/20
60000/60000 [==============================] - 7s 118us/step - loss: 0.0278 - acc: 0.9907 -
val_loss: 0.0581 - val_acc: 0.9834
Epoch 10/20
60000/60000 [==============================] - 7s 119us/step - loss: 0.0251 - acc: 0.9918 -
val_loss: 0.0612 - val_acc: 0.9826
Epoch 11/20
60000/60000 [==============================] - 7s 117us/step - loss: 0.0233 - acc: 0.9924 -
```

```
val_loss: 0.0565 - val_acc: 0.9844
Epoch 12/20
60000/60000 [==============================] - 7s 115us/step - loss: 0.0213 - acc: 0.9932 -
val_loss: 0.0627 - val_acc: 0.9838
Epoch 13/20
60000/60000 [==============================] - 7s 115us/step - loss: 0.0189 - acc: 0.9936 -
val_loss: 0.0589 - val_acc: 0.9842
Epoch 14/20
60000/60000 [==============================] - 7s 118us/step - loss: 0.0178 - acc: 0.9940 -
val_loss: 0.0610 - val_acc: 0.9833
Epoch 15/20
60000/60000 [==============================] - 7s 117us/step - loss: 0.0169 - acc: 0.9944 -
val_loss: 0.0622 - val_acc: 0.9845
Epoch 16/20
60000/60000 [==============================] - 7s 117us/step - loss: 0.0156 - acc: 0.9950 -
val_loss: 0.0578 - val_acc: 0.9858
Epoch 17/20
60000/60000 [==============================] - 7s 116us/step - loss: 0.0149 - acc: 0.9949 -
val_loss: 0.0613 - val_acc: 0.9852
Epoch 18/20
60000/60000 [==============================] - 7s 117us/step - loss: 0.0124 - acc: 0.9959 -
val_loss: 0.0621 - val_acc: 0.9855
Epoch 19/20
60000/60000 [==============================] - 7s 118us/step - loss: 0.0132 - acc: 0.9956 -
val_loss: 0.0648 - val_acc: 0.9834
Epoch 20/20
60000/60000 [==============================] - 7s 116us/step - loss: 0.0118 - acc: 0.9960 -
val_loss: 0.0598 - val_acc: 0.9845
Test score: 0.05980458545034853
Test accuracy: 0.9845
```





Above We got our test-loss > train-loss which is not a good performance

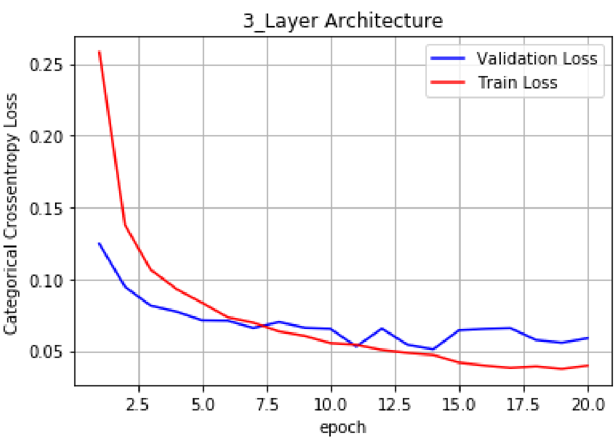
3 layer architecture Here below we experiment with one batch-normalization and 1 drop out layer at begining of the architecture with Adam optimizer and drop 0.5

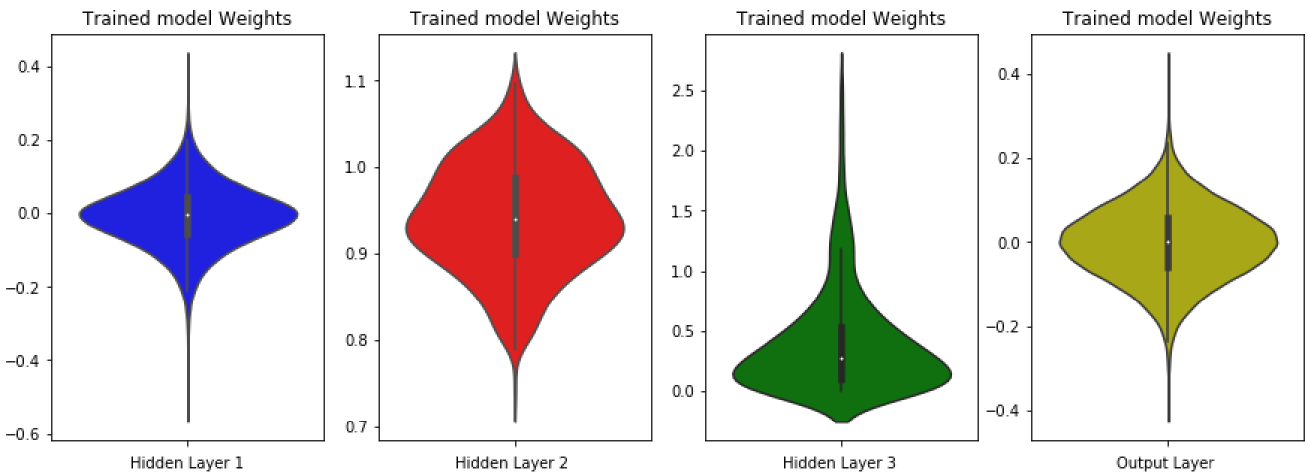
In [30]:

```
model_relu2 = Sequential()
#layer-1
model_relu2.add(Dense(500, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNo
rmal(mean=0.0, stddev=0.039, seed=None)))
#adding batch normalization
model_relu2.add(BatchNormalization())
#addding dropout rate
model_relu2.add(Dropout(0.5))
#layer-2
model_relu2.add(Dense(300, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.03
9, seed=None)))
#adding batch noramalization
#model_relu2.add(BatchNormalization())
#adding drop out rate
#model_relu2.add(Dropout(0.2))
#layer-3
model_relu2.add(Dense(200, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.03
9, seed=None)))
#adding batch noramalization
#model_relu2.add(BatchNormalization())
#adding drop out rate
#model_relu2.add(Dropout(0.2))

model_relu2.add(Dense(output_dim, activation='softmax'))


#print(model_relu2.summary())
#using optimizer adam
model_relu2.compile(optimizer='Adam', loss='categorical_crossentropy', metrics=['accuracy'])

history = model_relu2.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, vali
dation_data=(X_test, Y_test))

#---------------------------------------------------------------train and test error ---------------
-------------------------------------------------------------

score_4 = model_relu2.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score_4[0])
print('Test accuracy:', score_4[1])

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

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

vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
plt.title('3_Layer Architecture')
plt.show()

#---------------------------------------------------------------------layers performance -----------
---------------------------------------------------
w_after = model_relu2.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(figsize=(15,5))
plt.title("Weight matrices after model trained")

plt.subplot(1, 4, 1)

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

plt.subplot(1, 4, 2)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h2_w, color='r')
```

```
plt.xlabel('Hidden Layer 2 ')

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


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

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 6s 100us/step - loss: 0.2582 - acc: 0.9199 -
val_loss: 0.1245 - val_acc: 0.9590
Epoch 2/20
60000/60000 [==============================] - 5s 78us/step - loss: 0.1377 - acc: 0.9567 -
val_loss: 0.0946 - val_acc: 0.9697
Epoch 3/20
60000/60000 [==============================] - 5s 77us/step - loss: 0.1065 - acc: 0.9656 -
val_loss: 0.0814 - val_acc: 0.9732
Epoch 4/20
60000/60000 [==============================] - 5s 79us/step - loss: 0.0930 - acc: 0.9705 -
val_loss: 0.0773 - val_acc: 0.9764
Epoch 5/20
60000/60000 [==============================] - 5s 78us/step - loss: 0.0834 - acc: 0.9729 -
val_loss: 0.0712 - val_acc: 0.9787
Epoch 6/20
60000/60000 [==============================] - 5s 77us/step - loss: 0.0733 - acc: 0.9764 -
val_loss: 0.0709 - val_acc: 0.9786
Epoch 7/20
60000/60000 [==============================] - 5s 77us/step - loss: 0.0695 - acc: 0.9779 -
val_loss: 0.0658 - val_acc: 0.9802
Epoch 8/20
60000/60000 [==============================] - 5s 76us/step - loss: 0.0634 - acc: 0.9799 -
val_loss: 0.0700 - val_acc: 0.9786
Epoch 9/20
60000/60000 [==============================] - 5s 79us/step - loss: 0.0602 - acc: 0.9804 -
val_loss: 0.0660 - val_acc: 0.9803
Epoch 10/20
60000/60000 [==============================] - 5s 79us/step - loss: 0.0552 - acc: 0.9818 -
val_loss: 0.0653 - val_acc: 0.9819
Epoch 11/20
60000/60000 [==============================] - 5s 78us/step - loss: 0.0541 - acc: 0.9822 -
val_loss: 0.0529 - val_acc: 0.9839
Epoch 12/20
60000/60000 [==============================] - 5s 78us/step - loss: 0.0505 - acc: 0.9834 -
val_loss: 0.0654 - val_acc: 0.9802
Epoch 13/20
60000/60000 [==============================] - 5s 76us/step - loss: 0.0485 - acc: 0.9844 -
val_loss: 0.0541 - val_acc: 0.9853
Epoch 14/20
60000/60000 [==============================] - 5s 76us/step - loss: 0.0470 - acc: 0.9844 -
val_loss: 0.0509 - val_acc: 0.9848
Epoch 15/20
60000/60000 [==============================] - 5s 77us/step - loss: 0.0417 - acc: 0.9866 -
val_loss: 0.0643 - val_acc: 0.9828
Epoch 16/20
60000/60000 [==============================] - 5s 79us/step - loss: 0.0396 - acc: 0.9868 -
val_loss: 0.0652 - val_acc: 0.9820
Epoch 17/20
60000/60000 [==============================] - 5s 77us/step - loss: 0.0380 - acc: 0.9875 -
val_loss: 0.0658 - val_acc: 0.9827
Epoch 18/20
60000/60000 [==============================] - 5s 78us/step - loss: 0.0391 - acc: 0.9868 -
val_loss: 0.0575 - val_acc: 0.9838
Epoch 19/20
60000/60000 [==============================] - 5s 78us/step - loss: 0.0373 - acc: 0.9880 -
val_loss: 0.0555 - val_acc: 0.9851
Epoch 20/20
60000/60000 [==============================] - 5s 76us/step - loss: 0.0396 - acc: 0.9871 -
val_loss: 0.0587 - val_acc: 0.9839
Test score: 0.058732410513349896
Test accuracy: 0.9839
```





Above We got our test-loss > train-loss which is not a good performance

3 layer architecture Here below we experiment with one batch-normalization and 1 drop out layer at before last layer in the architecturer with Adam optimizer and drop 0.5

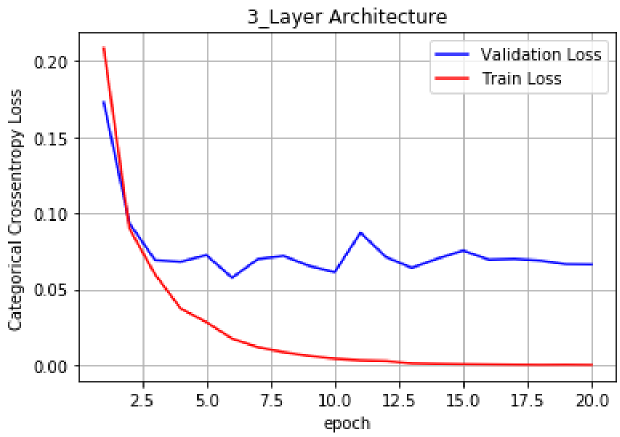
In [31]:

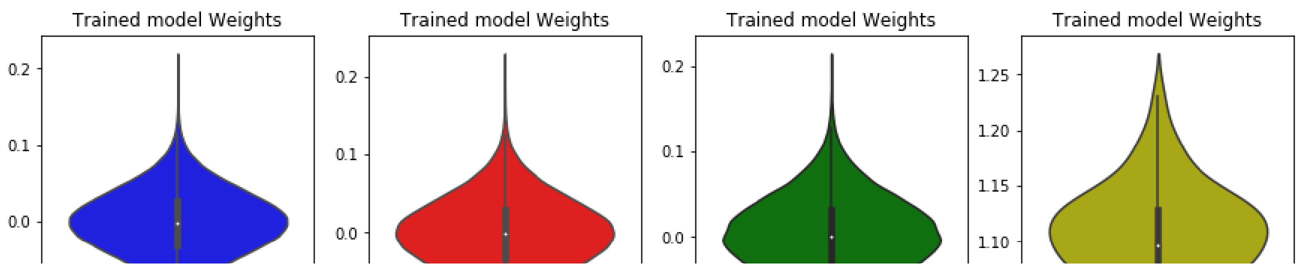
```
model_relu2 = Sequential()
#layer-1
model_relu2.add(Dense(500, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNo
rmal(mean=0.0, stddev=0.039, seed=None)))
#adding batch normalization
#model_relu2.add(BatchNormalization())
#addding dropout rate
#model_relu2.add(Dropout(0.2))
#layer-2
model_relu2.add(Dense(300, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.03
9, seed=None)))
#adding batch noramalization
#model_relu2.add(BatchNormalization())
#adding drop out rate
#model_relu2.add(Dropout(0.2))
#layer-3
model_relu2.add(Dense(200, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.03
9, seed=None)))
#adding batch noramalization
model_relu2.add(BatchNormalization())
#adding drop out rate
model_relu2.add(Dropout(0.2))

model_relu2.add(Dense(output_dim, activation='softmax'))


#print(model_relu2.summary())
#using optimizer adam
```

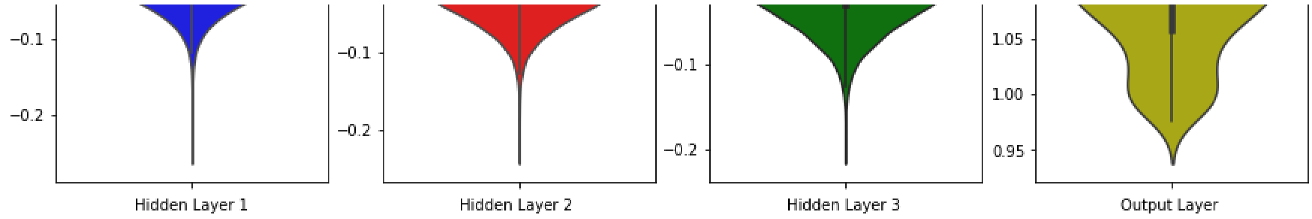
```
model_relu2.compile(optimizer='Adadelta', loss='categorical_crossentropy', metrics=['accuracy'])

history = model_relu2.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, vali
dation_data=(X_test, Y_test))

#---------------------------------------------------------------train and test error ----------------
-------------------------------------------------------------

score_4 = model_relu2.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score_4[0])
print('Test accuracy:', score_4[1])

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

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

vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
plt.title('3_Layer Architecture')
plt.show()

#---------------------------------------------------------------------layers performance ------------
---------------------------------------------------

w_after = model_relu2.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(figsize=(15,5))
plt.title("Weight matrices after model trained")

plt.subplot(1, 4, 1)

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

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

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


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

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 6s 107us/step - loss: 0.2086 - acc: 0.9362 -
val_loss: 0.1729 - val_acc: 0.9471
Epoch 2/20
60000/60000 [==============================] - 5s 82us/step - loss: 0.0899 - acc: 0.9725 -
val_loss: 0.0934 - val_acc: 0.9713
Epoch 3/20
60000/60000 [==============================] - 5s 79us/step - loss: 0.0596 - acc: 0.9809 -
val_loss: 0.0691 - val_acc: 0.9786
Epoch 4/20
60000/60000 [==============================] - 5s 80us/step - loss: 0.0372 - acc: 0.9879 -
val_loss: 0.0680 - val_acc: 0.9793
Epoch 5/20
60000/60000 [==============================] - 5s 81us/step - loss: 0.0282 - acc: 0.9910 -
```

```
val_loss: 0.0724 - val_acc: 0.9781
Epoch 6/20
60000/60000 [==============================] - 5s 78us/step - loss: 0.0173 - acc: 0.9945 -
val_loss: 0.0574 - val_acc: 0.9839
Epoch 7/20
60000/60000 [==============================] - 5s 78us/step - loss: 0.0117 - acc: 0.9962 -
val_loss: 0.0697 - val_acc: 0.9813
Epoch 8/20
60000/60000 [==============================] - 5s 79us/step - loss: 0.0085 - acc: 0.9974 -
val_loss: 0.0719 - val_acc: 0.9811
Epoch 9/20
60000/60000 [==============================] - 5s 78us/step - loss: 0.0060 - acc: 0.9981 -
val_loss: 0.0653 - val_acc: 0.9834
Epoch 10/20
60000/60000 [==============================] - 5s 79us/step - loss: 0.0041 - acc: 0.9989 -
val_loss: 0.0610 - val_acc: 0.9857
Epoch 11/20
60000/60000 [==============================] - 5s 78us/step - loss: 0.0031 - acc: 0.9991 -
val_loss: 0.0872 - val_acc: 0.9811
Epoch 12/20
60000/60000 [==============================] - 5s 79us/step - loss: 0.0027 - acc: 0.9992 -
val_loss: 0.0710 - val_acc: 0.9838
Epoch 13/20
60000/60000 [==============================] - 5s 77us/step - loss: 0.0011 - acc: 0.9998 -
val_loss: 0.0640 - val_acc: 0.9856
Epoch 14/20
60000/60000 [==============================] - 5s 78us/step - loss: 7.5832e-04 - acc: 0.9998 - val
_loss: 0.0700 - val_acc: 0.9856
Epoch 15/20
60000/60000 [==============================] - 5s 79us/step - loss: 5.3548e-04 - acc: 0.9998 - val
_loss: 0.0754 - val_acc: 0.9850
Epoch 16/20
60000/60000 [==============================] - 5s 78us/step - loss: 3.6343e-04 - acc: 0.9999 - val
_loss: 0.0694 - val_acc: 0.9865
Epoch 17/20
60000/60000 [==============================] - 5s 78us/step - loss: 2.0863e-04 - acc: 1.0000 - val
_loss: 0.0699 - val_acc: 0.9860
Epoch 18/20
60000/60000 [==============================] - 5s 78us/step - loss: 7.5309e-05 - acc: 1.0000 - val
_loss: 0.0688 - val_acc: 0.9867
Epoch 19/20
60000/60000 [==============================] - 5s 79us/step - loss: 1.6480e-04 - acc: 1.0000 - val
_loss: 0.0664 - val_acc: 0.9866
Epoch 20/20
60000/60000 [==============================] - 5s 77us/step - loss: 3.2577e-05 - acc: 1.0000 - val
_loss: 0.0662 - val_acc: 0.9866
Test score: 0.06620450230908602
Test accuracy: 0.9866
```







Above We got our test-loss > train-loss which is not a good performance

5-layer Architecture with Batch-Normalization and Dropout

In [32]:

```
model_relu3 = Sequential()
#layer-1
model_relu3.add(Dense(500, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNo
rmal(mean=0.0, stddev=0.039, seed=None)))
#adding batch normalization
model_relu3.add(BatchNormalization())
#addding dropout rate
model_relu3.add(Dropout(0.5))
#layer-2
model_relu3.add(Dense(400, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.03
9, seed=None)))
#adding batch noramalization
model_relu3.add(BatchNormalization())
#adding drop out rate
model_relu3.add(Dropout(0.5))
#layer-3
model_relu3.add(Dense(300, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.03
9, seed=None)))
#adding batch noramalization
model_relu3.add(BatchNormalization())
#adding drop out rate
model_relu3.add(Dropout(0.5))
#layer-4
model_relu3.add(Dense(200, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.03
9, seed=None)))
#adding batch noramalization
model_relu3.add(BatchNormalization())
#adding drop out rate
model_relu3.add(Dropout(0.5))
#layer-5
model_relu3.add(Dense(100, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.03
9, seed=None)))
#adding batch noramalization
model_relu3.add(BatchNormalization())
#adding drop out rate
model_relu3.add(Dropout(0.5))

model_relu3.add(Dense(output_dim, activation='softmax'))


#print(model_relu3.summary())
#using optimizer adam
model_relu3.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history = model_relu3.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, vali
dation_data=(X_test, Y_test))
```

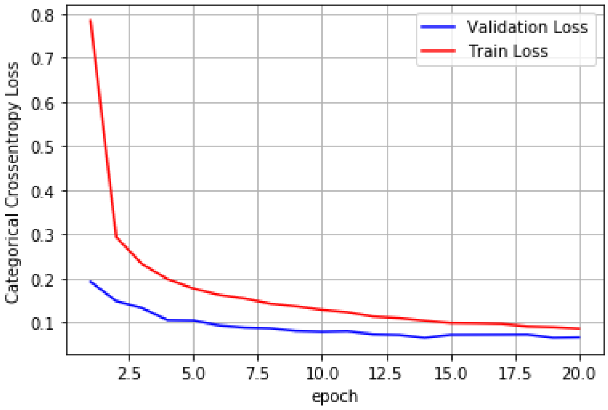
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 12s 204us/step - loss: 0.7834 - acc: 0.7620 - val_l
oss: 0.1921 - val_acc: 0.9478
Epoch 2/20
60000/60000 [==============================] - 10s 159us/step - loss: 0.2929 - acc: 0.9170 - val_l
oss: 0.1483 - val_acc: 0.9584
Epoch 3/20
60000/60000 [==============================] - 9s 157us/step - loss: 0.2324 - acc: 0.9356 -
val_loss: 0.1326 - val_acc: 0.9636
Epoch 4/20
```

```
Epoch 4/20
60000/60000 [==============================] - 10s 159us/step - loss: 0.1981 - acc: 0.9460 - val_l
oss: 0.1052 - val_acc: 0.9697
Epoch 5/20
60000/60000 [==============================] - 10s 160us/step - loss: 0.1768 - acc: 0.9519 - val_l
oss: 0.1044 - val_acc: 0.9709
Epoch 6/20
60000/60000 [==============================] - 10s 160us/step - loss: 0.1624 - acc: 0.9551 - val_l
oss: 0.0932 - val_acc: 0.9753
Epoch 7/20
60000/60000 [==============================] - 10s 160us/step - loss: 0.1541 - acc: 0.9577 - val_l
oss: 0.0882 - val_acc: 0.9746
Epoch 8/20
60000/60000 [==============================] - 10s 159us/step - loss: 0.1425 - acc: 0.9607 - val_l
oss: 0.0866 - val_acc: 0.9761
Epoch 9/20
60000/60000 [==============================] - 9s 158us/step - loss: 0.1364 - acc: 0.9633 -
val_loss: 0.0806 - val_acc: 0.9770
Epoch 10/20
60000/60000 [==============================] - 9s 158us/step - loss: 0.1285 - acc: 0.9648 -
val_loss: 0.0789 - val_acc: 0.9783
Epoch 11/20
60000/60000 [==============================] - 10s 159us/step - loss: 0.1230 - acc: 0.9665 - val_l
oss: 0.0801 - val_acc: 0.9792
Epoch 12/20
60000/60000 [==============================] - 9s 158us/step - loss: 0.1134 - acc: 0.9688 -
val_loss: 0.0730 - val_acc: 0.9806
Epoch 13/20
60000/60000 [==============================] - 9s 157us/step - loss: 0.1098 - acc: 0.9697 -
val_loss: 0.0716 - val_acc: 0.9796
Epoch 14/20
60000/60000 [==============================] - 9s 157us/step - loss: 0.1039 - acc: 0.9717 -
val_loss: 0.0650 - val_acc: 0.9823
Epoch 15/20
60000/60000 [==============================] - 9s 158us/step - loss: 0.0987 - acc: 0.9736 -
val_loss: 0.0720 - val_acc: 0.9812
Epoch 16/20
60000/60000 [==============================] - 9s 157us/step - loss: 0.0980 - acc: 0.9731 -
val_loss: 0.0722 - val_acc: 0.9804
Epoch 17/20
60000/60000 [==============================] - 10s 160us/step - loss: 0.0968 - acc: 0.9738 - val_l
oss: 0.0723 - val_acc: 0.9813
Epoch 18/20
60000/60000 [==============================] - 10s 159us/step - loss: 0.0908 - acc: 0.9747 - val_l
oss: 0.0726 - val_acc: 0.9811
Epoch 19/20
60000/60000 [==============================] - 10s 159us/step - loss: 0.0891 - acc: 0.9759 - val_l
oss: 0.0651 - val_acc: 0.9824
Epoch 20/20
60000/60000 [==============================] - 9s 158us/step - loss: 0.0861 - acc: 0.9767 -
val_loss: 0.0660 - val_acc: 0.9824
```

In [33]:

```python
score_6 = model_relu3.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score_6[0])
print('Test accuracy:', score_6[1])

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

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

vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
plt.title('5_Layer Architecture')
plt.show()
```

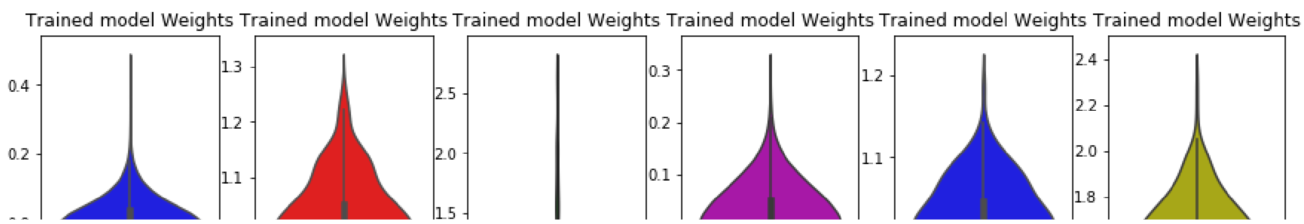
```
Test score: 0.066039138047304
Test accuracy: 0.9824
```

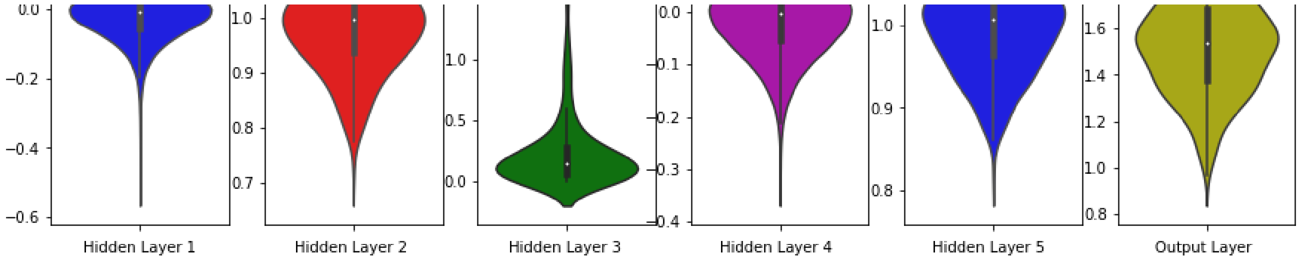


In above plot it maintains smaller error distance from train to test

In [34]:

```
w_after = model_relu3.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(figsize=(15,5))
plt.title("Weight matrices after model trained")

plt.subplot(1, 6, 1,)

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

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

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


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

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

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





5-layer Architecture with-out Batch-Normalization and Dropout

In [35]:

```
model_relu3 = Sequential()
#layer-1
model_relu3.add(Dense(500, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNo
rmal(mean=0.0, stddev=0.039, seed=None)))
#adding batch normalization
#model_relu3.add(BatchNormalization())
#addding dropout rate
#model_relu3.add(Dropout(0.5))
#layer-2
model_relu3.add(Dense(400, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.03
9, seed=None)))
#adding batch noramalization
#model_relu3.add(BatchNormalization())
#adding drop out rate
#model_relu3.add(Dropout(0.5))
#layer-3
model_relu3.add(Dense(300, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.03
9, seed=None)))
#adding batch noramalization
#model_relu3.add(BatchNormalization())
#adding drop out rate
#model_relu3.add(Dropout(0.5))
#layer-4
model_relu3.add(Dense(200, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.03
9, seed=None)))
#adding batch noramalization
#model_relu3.add(BatchNormalization())
#adding drop out rate
#model_relu3.add(Dropout(0.5))
#layer-5
model_relu3.add(Dense(100, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.03
9, seed=None)))
#adding batch noramalization
#model_relu3.add(BatchNormalization())
#adding drop out rate
#model_relu3.add(Dropout(0.5))

model_relu3.add(Dense(output_dim, activation='softmax'))


#print(model_relu3.summary())
#using optimizer adam
model_relu3.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history = model_relu3.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, vali
dation_data=(X_test, Y_test))
```

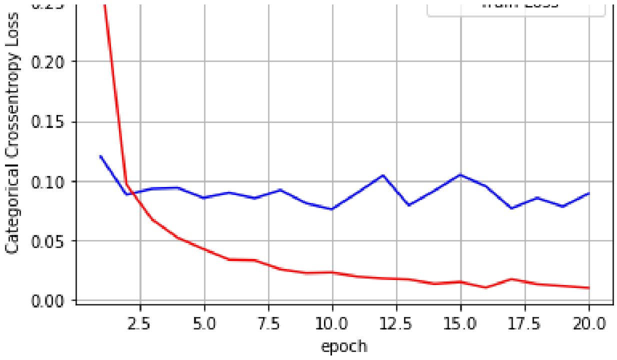
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 6s 102us/step - loss: 0.2755 - acc: 0.9157 -
val_loss: 0.1198 - val_acc: 0.9652
Epoch 2/20
60000/60000 [==============================] - 4s 71us/step - loss: 0.0965 - acc: 0.9713 -
val_loss: 0.0879 - val_acc: 0.9747
Epoch 3/20
60000/60000 [==============================] - 4s 75us/step - loss: 0.0673 - acc: 0.9796 -
val_loss: 0.0929 - val_acc: 0.9732
Epoch 4/20
60000/60000 [==============================] - 4s 74us/step - loss: 0.0518 - acc: 0.9842 -
```

```
val_loss: 0.0936 - val_acc: 0.9757
Epoch 5/20
60000/60000 [==============================] - 4s 72us/step - loss: 0.0424 - acc: 0.9868 -
val_loss: 0.0852 - val_acc: 0.9759
Epoch 6/20
60000/60000 [==============================] - 4s 75us/step - loss: 0.0334 - acc: 0.9897 -
val_loss: 0.0896 - val_acc: 0.9745
Epoch 7/20
60000/60000 [==============================] - 4s 73us/step - loss: 0.0329 - acc: 0.9901 -
val_loss: 0.0849 - val_acc: 0.9805
Epoch 8/20
60000/60000 [==============================] - 4s 72us/step - loss: 0.0253 - acc: 0.9918 -
val_loss: 0.0918 - val_acc: 0.9776
Epoch 9/20
60000/60000 [==============================] - 4s 72us/step - loss: 0.0222 - acc: 0.9934 -
val_loss: 0.0807 - val_acc: 0.9802
Epoch 10/20
60000/60000 [==============================] - 4s 72us/step - loss: 0.0227 - acc: 0.9936 -
val_loss: 0.0757 - val_acc: 0.9822
Epoch 11/20
60000/60000 [==============================] - 4s 72us/step - loss: 0.0193 - acc: 0.9941 -
val_loss: 0.0896 - val_acc: 0.9791
Epoch 12/20
60000/60000 [==============================] - 4s 71us/step - loss: 0.0177 - acc: 0.9945 -
val_loss: 0.1042 - val_acc: 0.9775
Epoch 13/20
60000/60000 [==============================] - 4s 71us/step - loss: 0.0169 - acc: 0.9952 -
val_loss: 0.0790 - val_acc: 0.9827
Epoch 14/20
60000/60000 [==============================] - 4s 72us/step - loss: 0.0132 - acc: 0.9958 -
val_loss: 0.0913 - val_acc: 0.9803
Epoch 15/20
60000/60000 [==============================] - 4s 73us/step - loss: 0.0148 - acc: 0.9958 -
val_loss: 0.1047 - val_acc: 0.9772
Epoch 16/20
60000/60000 [==============================] - 4s 72us/step - loss: 0.0100 - acc: 0.9970 -
val_loss: 0.0950 - val_acc: 0.9831
Epoch 17/20
60000/60000 [==============================] - 4s 72us/step - loss: 0.0171 - acc: 0.9954 -
val_loss: 0.0764 - val_acc: 0.9817
Epoch 18/20
60000/60000 [==============================] - 4s 72us/step - loss: 0.0129 - acc: 0.9965 -
val_loss: 0.0852 - val_acc: 0.9828
Epoch 19/20
60000/60000 [==============================] - 4s 71us/step - loss: 0.0114 - acc: 0.9968 -
val_loss: 0.0780 - val_acc: 0.9827
Epoch 20/20
60000/60000 [==============================] - 4s 72us/step - loss: 0.0097 - acc: 0.9973 -
val_loss: 0.0888 - val_acc: 0.9830
```

In [36]:

```python
score_6 = model_relu3.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score_6[0])
print('Test accuracy:', score_6[1])

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

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

vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
plt.title('5_Layer Architecture')
plt.show()
```

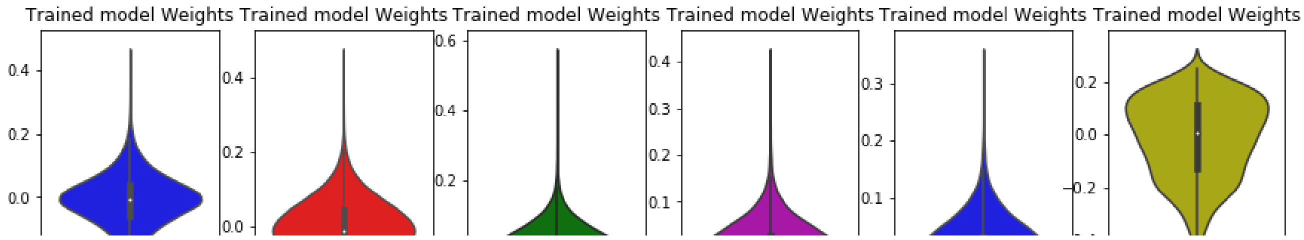
```
Test score: 0.08883313840526234
Test accuracy: 0.983
```

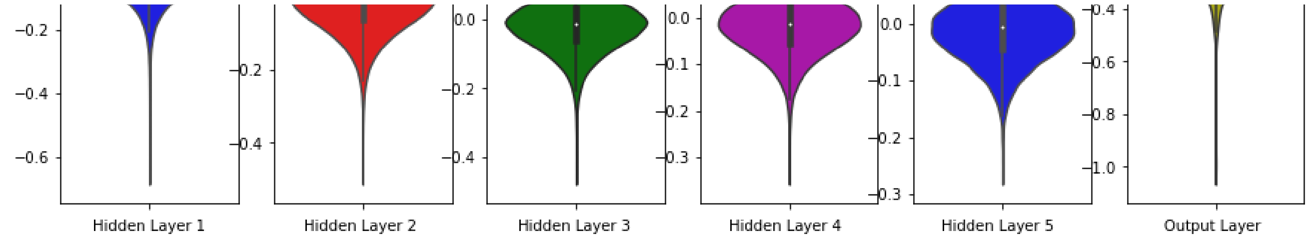


Here we see that in above plot with out apply of batch-normalization and drop out we got test loss > train loss

In [37]:

```
w_after = model_relu3.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(figsize=(15,5))
plt.title("Weight matrices after model trained")

plt.subplot(1, 6, 1,)

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

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

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


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

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

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





5 layer architecture We also experiment with Different optimizer like Adadelta with different drop-out rate 0.2

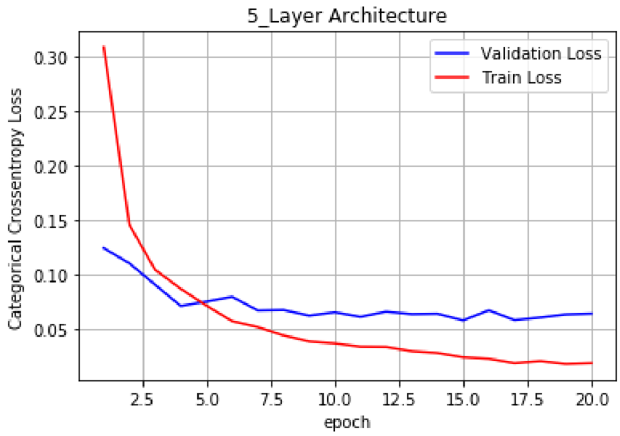
In [38]:

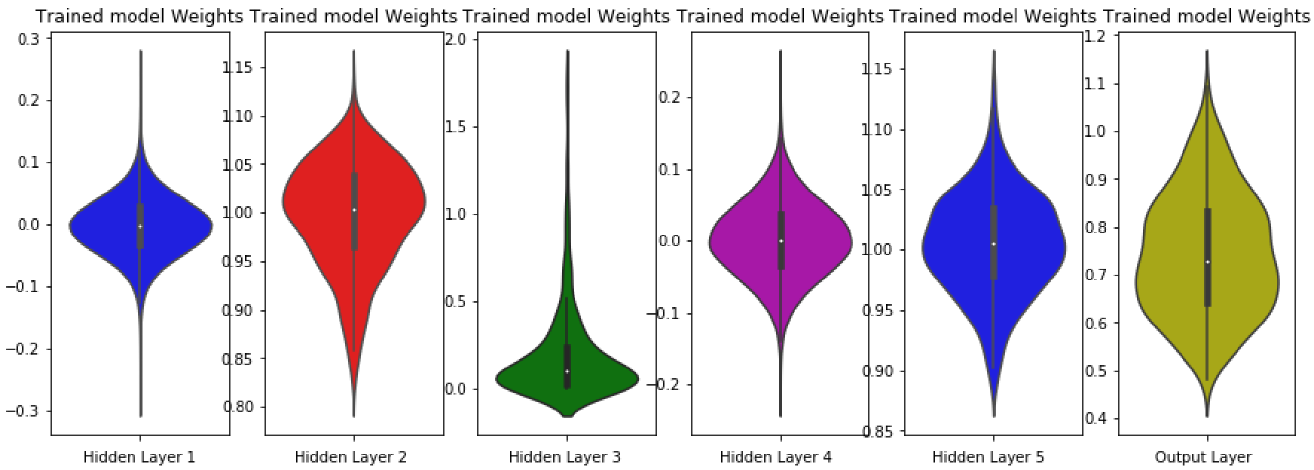
```
model_relu3 = Sequential()
#layer-1
model_relu3.add(Dense(500, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNo
rmal(mean=0.0, stddev=0.039, seed=None)))
#adding batch normalization
model_relu3.add(BatchNormalization())
#addding dropout rate
model_relu3.add(Dropout(0.2))
#layer-2
model_relu3.add(Dense(400, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.03
9, seed=None)))
#adding batch noramalization
model_relu3.add(BatchNormalization())
#adding drop out rate
model_relu3.add(Dropout(0.2))
#layer-3
model_relu3.add(Dense(300, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.03
9, seed=None)))
#adding batch noramalization
model_relu3.add(BatchNormalization())
#adding drop out rate
model_relu3.add(Dropout(0.2))
#layer-4
model_relu3.add(Dense(200, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.03
9, seed=None)))
#adding batch noramalization
model_relu3.add(BatchNormalization())
#adding drop out rate
model_relu3.add(Dropout(0.2))
#layer-5
model_relu3.add(Dense(100, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.03
9, seed=None)))
#adding batch noramalization
model_relu3.add(BatchNormalization())
#adding drop out rate
model_relu3.add(Dropout(0.2))

model_relu3.add(Dense(output_dim, activation='softmax'))


#print(model_relu3.summary())
#using optimizer adam
model_relu3.compile(optimizer='Adadelta', loss='categorical_crossentropy', metrics=['accuracy'])

history = model_relu3.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, vali
dation_data=(X_test, Y_test))
#---------------------------------------------------------------------------------------------------
-----------------------------------
score_6 = model_relu3.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score_6[0])
print('Test accuracy:', score_6[1])

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

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

vy = history.history['val_loss']
```

```
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
plt.title('5_Layer Architecture')
plt.show()

#--------------------------------------------------------------------------------------------------
------------------------------------
w_after = model_relu3.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(figsize=(15,5))
plt.title("Weight matrices after model trained")

plt.subplot(1, 6, 1,)

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

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

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


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

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

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

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 13s 219us/step - loss: 0.3082 - acc: 0.9069 - val_l
oss: 0.1241 - val_acc: 0.9633
Epoch 2/20
60000/60000 [==============================] - 10s 166us/step - loss: 0.1455 - acc: 0.9573 - val_l
oss: 0.1102 - val_acc: 0.9685
Epoch 3/20
60000/60000 [==============================] - 10s 167us/step - loss: 0.1043 - acc: 0.9689 - val_l
oss: 0.0906 - val_acc: 0.9729
Epoch 4/20
60000/60000 [==============================] - 10s 167us/step - loss: 0.0869 - acc: 0.9738 - val_l
oss: 0.0711 - val_acc: 0.9789
Epoch 5/20
60000/60000 [==============================] - 10s 167us/step - loss: 0.0715 - acc: 0.9776 - val_l
oss: 0.0752 - val_acc: 0.9792
Epoch 6/20
60000/60000 [==============================] - 10s 165us/step - loss: 0.0572 - acc: 0.9829 - val_l
oss: 0.0795 - val_acc: 0.9771
Epoch 7/20
60000/60000 [==============================] - 10s 168us/step - loss: 0.0518 - acc: 0.9847 - val_l
oss: 0.0670 - val_acc: 0.9812
Epoch 8/20
```

```
60000/60000 [==============================] - 10s 168us/step - loss: 0.0441 - acc: 0.9863 - val_l
oss: 0.0675 - val_acc: 0.9810
Epoch 9/20
60000/60000 [==============================] - 10s 166us/step - loss: 0.0386 - acc: 0.9882 - val_l
oss: 0.0622 - val_acc: 0.9833
Epoch 10/20
60000/60000 [==============================] - 10s 167us/step - loss: 0.0368 - acc: 0.9886 - val_l
oss: 0.0653 - val_acc: 0.9815
Epoch 11/20
60000/60000 [==============================] - 10s 167us/step - loss: 0.0338 - acc: 0.9895 - val_l
oss: 0.0612 - val_acc: 0.9839
Epoch 12/20
60000/60000 [==============================] - 10s 165us/step - loss: 0.0336 - acc: 0.9896 - val_l
oss: 0.0659 - val_acc: 0.9818
Epoch 13/20
60000/60000 [==============================] - 10s 168us/step - loss: 0.0297 - acc: 0.9908 - val_l
oss: 0.0636 - val_acc: 0.9848
Epoch 14/20
60000/60000 [==============================] - 10s 167us/step - loss: 0.0281 - acc: 0.9915 - val_l
oss: 0.0639 - val_acc: 0.9827
Epoch 15/20
60000/60000 [==============================] - 10s 166us/step - loss: 0.0242 - acc: 0.9924 - val_l
oss: 0.0579 - val_acc: 0.9846
Epoch 16/20
60000/60000 [==============================] - 10s 167us/step - loss: 0.0228 - acc: 0.9929 - val_l
oss: 0.0672 - val_acc: 0.9835
Epoch 17/20
60000/60000 [==============================] - 10s 167us/step - loss: 0.0187 - acc: 0.9940 - val_l
oss: 0.0582 - val_acc: 0.9860
Epoch 18/20
60000/60000 [==============================] - 10s 167us/step - loss: 0.0206 - acc: 0.9937 - val_l
oss: 0.0606 - val_acc: 0.9859
Epoch 19/20
60000/60000 [==============================] - 10s 166us/step - loss: 0.0180 - acc: 0.9941 - val_l
oss: 0.0633 - val_acc: 0.9851
Epoch 20/20
60000/60000 [==============================] - 10s 169us/step - loss: 0.0188 - acc: 0.9940 - val_l
oss: 0.0641 - val_acc: 0.9845
Test score: 0.06405649431259226
Test accuracy: 0.9845
```





Above We got our test-loss > train-loss which is not a good performance

5 layer architecture Here below we experiment with one batch-normalization and 1 drop out layer in the begining of the architecture it means after first layer with Adam optimizer

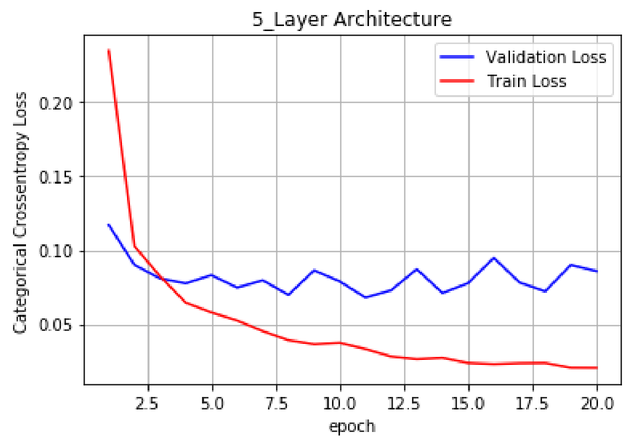
In [39]:

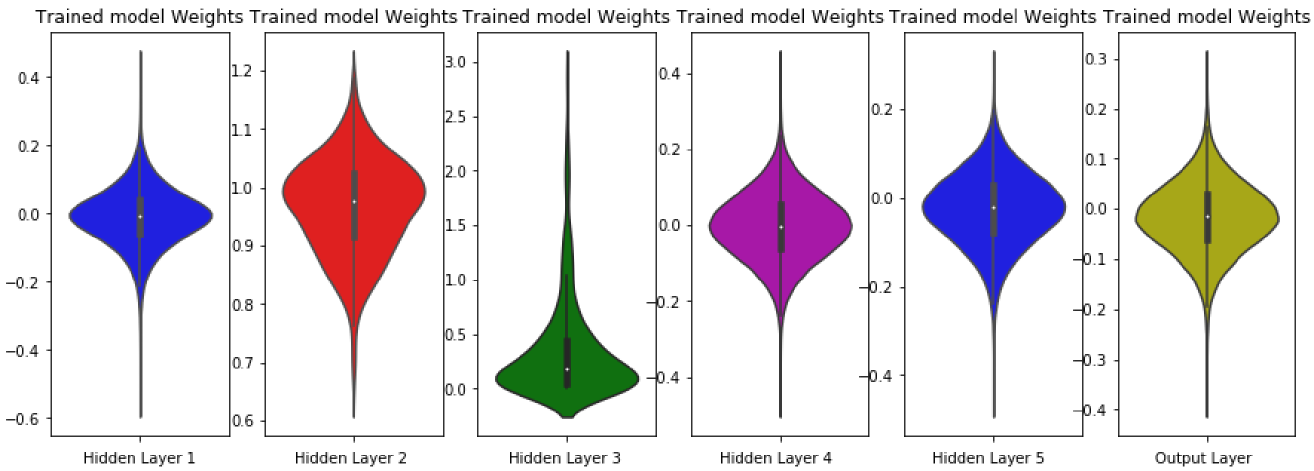
```
model_relu3 = Sequential()
#layer-1
model_relu3.add(Dense(500, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNo
rmal(mean=0.0, stddev=0.039, seed=None)))
#adding batch normalization
model_relu3.add(BatchNormalization())
#addding dropout rate
model_relu3.add(Dropout(0.2))
#layer-2
model_relu3.add(Dense(400, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.03
9, seed=None)))
#adding batch noramalization
#model_relu3.add(BatchNormalization())
#adding drop out rate
#model_relu3.add(Dropout(0.2))
#layer-3
model_relu3.add(Dense(300, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.03
9, seed=None)))
#adding batch noramalization
#model_relu3.add(BatchNormalization())
#adding drop out rate
#model_relu3.add(Dropout(0.2))
#layer-4
model_relu3.add(Dense(200, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.03
9, seed=None)))
#adding batch noramalization
#model_relu3.add(BatchNormalization())
#adding drop out rate
#model_relu3.add(Dropout(0.2))
#layer-5
model_relu3.add(Dense(100, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.03
9, seed=None)))
#adding batch noramalization
#model_relu3.add(BatchNormalization())
#adding drop out rate
#model_relu3.add(Dropout(0.2))

model_relu3.add(Dense(output_dim, activation='softmax'))


#print(model_relu3.summary())
#using optimizer adam
model_relu3.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history = model_relu3.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, vali
dation_data=(X_test, Y_test))
#---------------------------------------------------------------------------------------------------
----------------------------------
score_6 = model_relu3.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score_6[0])
print('Test accuracy:', score_6[1])

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

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

vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
plt.title('5_Layer Architecture')
plt.show()
```

```
#------------------------------------------------------------------------------------------------------------------------------------
w_after = model_relu3.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(figsize=(15,5))
plt.title("Weight matrices after model trained")

plt.subplot(1, 6, 1,)

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

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

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


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

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

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

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 8s 136us/step - loss: 0.2350 - acc: 0.9285 -
val_loss: 0.1170 - val_acc: 0.9640
Epoch 2/20
60000/60000 [==============================] - 6s 94us/step - loss: 0.1027 - acc: 0.9687 -
val_loss: 0.0900 - val_acc: 0.9729
Epoch 3/20
60000/60000 [==============================] - 6s 98us/step - loss: 0.0822 - acc: 0.9754 -
val_loss: 0.0808 - val_acc: 0.9775
Epoch 4/20
60000/60000 [==============================] - 6s 101us/step - loss: 0.0644 - acc: 0.9800 -
val_loss: 0.0775 - val_acc: 0.9770
Epoch 5/20
60000/60000 [==============================] - 6s 98us/step - loss: 0.0578 - acc: 0.9825 -
val_loss: 0.0830 - val_acc: 0.9767
Epoch 6/20
60000/60000 [==============================] - 6s 94us/step - loss: 0.0523 - acc: 0.9841 -
val_loss: 0.0746 - val_acc: 0.9776
Epoch 7/20
60000/60000 [==============================] - 6s 94us/step - loss: 0.0451 - acc: 0.9862 -
val_loss: 0.0795 - val_acc: 0.9793
Epoch 8/20
60000/60000 [==============================] - 6s 94us/step - loss: 0.0390 - acc: 0.9881 -
val_loss: 0.0697 - val_acc: 0.9809
Epoch 9/20
60000/60000 [==============================] - 6s 96us/step - loss: 0.0363 - acc: 0.9886 -
val_loss: 0.0862 - val_acc: 0.9757
Epoch 10/20
```

```
Epoch 10/20
60000/60000 [==============================] - 6s 95us/step - loss: 0.0372 - acc: 0.9885 -
val_loss: 0.0788 - val_acc: 0.9805
Epoch 11/20
60000/60000 [==============================] - 6s 93us/step - loss: 0.0330 - acc: 0.9898 -
val_loss: 0.0679 - val_acc: 0.9829
Epoch 12/20
60000/60000 [==============================] - 6s 94us/step - loss: 0.0280 - acc: 0.9910 -
val_loss: 0.0728 - val_acc: 0.9834
Epoch 13/20
60000/60000 [==============================] - 6s 95us/step - loss: 0.0262 - acc: 0.9918 -
val_loss: 0.0870 - val_acc: 0.9826
Epoch 14/20
60000/60000 [==============================] - 6s 95us/step - loss: 0.0271 - acc: 0.9917 -
val_loss: 0.0709 - val_acc: 0.9821
Epoch 15/20
60000/60000 [==============================] - 6s 95us/step - loss: 0.0236 - acc: 0.9927 -
val_loss: 0.0776 - val_acc: 0.9829
Epoch 16/20
60000/60000 [==============================] - 6s 94us/step - loss: 0.0228 - acc: 0.9929 -
val_loss: 0.0948 - val_acc: 0.9818
Epoch 17/20
60000/60000 [==============================] - 6s 94us/step - loss: 0.0234 - acc: 0.9929 -
val_loss: 0.0781 - val_acc: 0.9824
Epoch 18/20
60000/60000 [==============================] - 6s 94us/step - loss: 0.0236 - acc: 0.9930 -
val_loss: 0.0721 - val_acc: 0.9818
Epoch 19/20
60000/60000 [==============================] - 6s 96us/step - loss: 0.0204 - acc: 0.9939 -
val_loss: 0.0899 - val_acc: 0.9791
Epoch 20/20
60000/60000 [==============================] - 6s 97us/step - loss: 0.0203 - acc: 0.9940 -
val_loss: 0.0857 - val_acc: 0.9807
Test score: 0.08574480261191275
Test accuracy: 0.9807
```





Above We got our test-loss > train-loss which is not a good performance

5 layer architecture Here below we experiment with one batch-normalization and 1 drop out layer in the before last layer of the architecture with Adam optimizer and drop 0.5

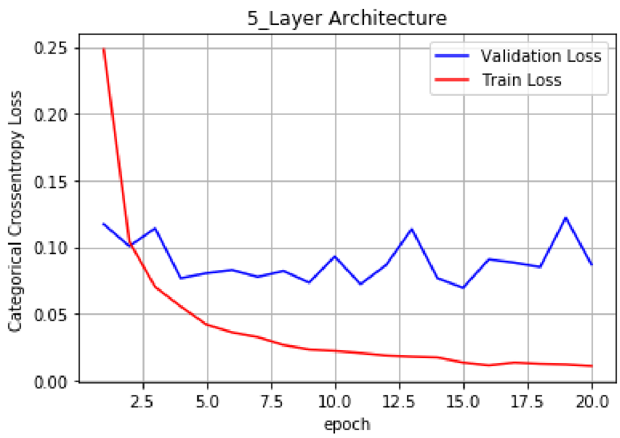
In [40]:

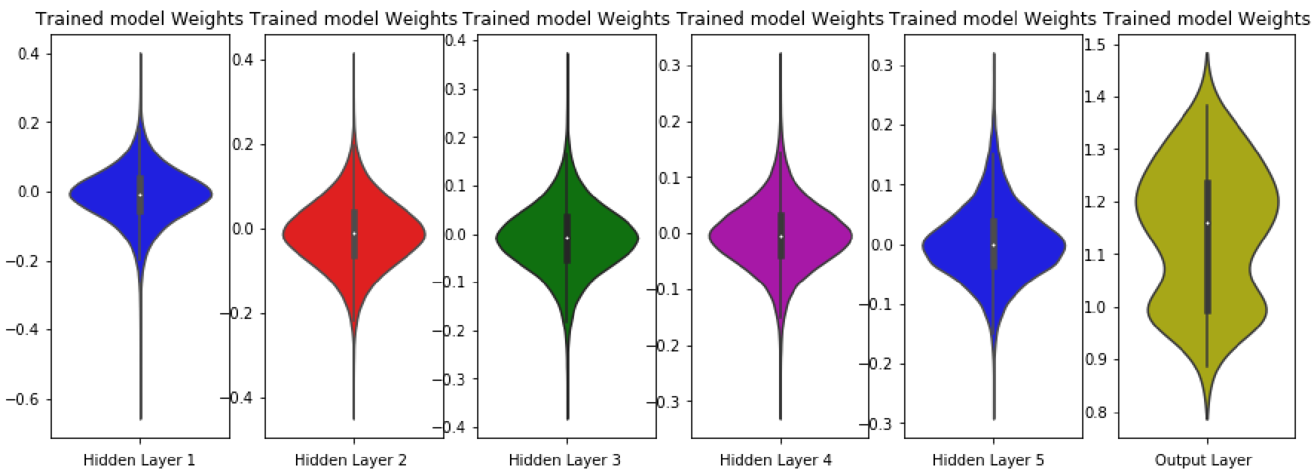
```
model_relu3 = Sequential()
#layer-1
model_relu3.add(Dense(500, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNo
rmal(mean=0.0, stddev=0.039, seed=None)))
#adding batch normalization
#model_relu3.add(BatchNormalization())
#addding dropout rate
#model_relu3.add(Dropout(0.2))
#layer-2
model_relu3.add(Dense(400, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.03
9, seed=None)))
#adding batch noramalization
#model_relu3.add(BatchNormalization())
#adding drop out rate
#model_relu3.add(Dropout(0.2))
#layer-3
model_relu3.add(Dense(300, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.03
9, seed=None)))
#adding batch noramalization
#model_relu3.add(BatchNormalization())
#adding drop out rate
#model_relu3.add(Dropout(0.2))
#layer-4
model_relu3.add(Dense(200, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.03
9, seed=None)))
#adding batch noramalization
#model_relu3.add(BatchNormalization())
#adding drop out rate
#model_relu3.add(Dropout(0.2))
#layer-5
model_relu3.add(Dense(100, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.03
9, seed=None)))
#adding batch noramalization
model_relu3.add(BatchNormalization())
#adding drop out rate
model_relu3.add(Dropout(0.5))

model_relu3.add(Dense(output_dim, activation='softmax'))


#print(model_relu3.summary())
#using optimizer adam
model_relu3.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history = model_relu3.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, vali
dation_data=(X_test, Y_test))
#----------------------------------------------------------------------------------------------------
-----------------------------------
score_6 = model_relu3.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score_6[0])
print('Test accuracy:', score_6[1])

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

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

vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
plt.title('5_Layer Architecture')
plt.show()

#----------------------------------------------------------------------------------------------------
------------------------------------

w_after = model_relu3.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(figsize=(15,5))
plt.title("Weight matrices after model trained")

plt.subplot(1, 6, 1,)

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

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

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


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

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

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

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 8s 133us/step - loss: 0.2481 - acc: 0.9283 -
val_loss: 0.1171 - val_acc: 0.9651
Epoch 2/20
60000/60000 [==============================] - 5s 89us/step - loss: 0.1040 - acc: 0.9715 -
val_loss: 0.1006 - val_acc: 0.9705
Epoch 3/20
60000/60000 [==============================] - 5s 88us/step - loss: 0.0701 - acc: 0.9800 -
val_loss: 0.1140 - val_acc: 0.9672
Epoch 4/20
60000/60000 [==============================] - 5s 90us/step - loss: 0.0554 - acc: 0.9841 -
val_loss: 0.0765 - val_acc: 0.9790
Epoch 5/20
60000/60000 [==============================] - 5s 90us/step - loss: 0.0418 - acc: 0.9883 -
val_loss: 0.0803 - val_acc: 0.9797
Epoch 6/20
60000/60000 [==============================] - 5s 88us/step - loss: 0.0359 - acc: 0.9893 -
val_loss: 0.0827 - val_acc: 0.9787
Epoch 7/20
60000/60000 [==============================] - 5s 89us/step - loss: 0.0324 - acc: 0.9901 -
val_loss: 0.0775 - val_acc: 0.9795
Epoch 8/20
60000/60000 [==============================] - 5s 89us/step - loss: 0.0265 - acc: 0.9923 -
val_loss: 0.0820 - val_acc: 0.9793
Epoch 9/20
60000/60000 [==============================] - 5s 90us/step - loss: 0.0231 - acc: 0.9935 -
val_loss: 0.0733 - val_acc: 0.9820
Epoch 10/20
60000/60000 [==============================] - 5s 90us/step - loss: 0.0221 - acc: 0.9935 -
val_loss: 0.0929 - val_acc: 0.9799
Epoch 11/20
60000/60000 [==============================] - 5s 91us/step - loss: 0.0205 - acc: 0.9944 -
```

```
val_loss: 0.0721 - val_acc: 0.9828
Epoch 12/20
60000/60000 [==============================] - 5s 89us/step - loss: 0.0186 - acc: 0.9946 -
val_loss: 0.0864 - val_acc: 0.9794
Epoch 13/20
60000/60000 [==============================] - 5s 89us/step - loss: 0.0178 - acc: 0.9948 -
val_loss: 0.1135 - val_acc: 0.9725
Epoch 14/20
60000/60000 [==============================] - 5s 89us/step - loss: 0.0172 - acc: 0.9950 -
val_loss: 0.0766 - val_acc: 0.9804
Epoch 15/20
60000/60000 [==============================] - 5s 90us/step - loss: 0.0133 - acc: 0.9964 -
val_loss: 0.0693 - val_acc: 0.9838
Epoch 16/20
60000/60000 [==============================] - 5s 90us/step - loss: 0.0112 - acc: 0.9968 -
val_loss: 0.0907 - val_acc: 0.9799
Epoch 17/20
60000/60000 [==============================] - 5s 89us/step - loss: 0.0133 - acc: 0.9962 -
val_loss: 0.0882 - val_acc: 0.9805
Epoch 18/20
60000/60000 [==============================] - 5s 89us/step - loss: 0.0123 - acc: 0.9968 -
val_loss: 0.0850 - val_acc: 0.9818
Epoch 19/20
60000/60000 [==============================] - 5s 89us/step - loss: 0.0119 - acc: 0.9963 -
val_loss: 0.1220 - val_acc: 0.9759
Epoch 20/20
60000/60000 [==============================] - 5s 89us/step - loss: 0.0107 - acc: 0.9969 -
val_loss: 0.0869 - val_acc: 0.9829
Test score: 0.08687413363270534
Test accuracy: 0.9829
```





Above We got our test-loss > train-loss which is not a good performance

In [44]:

```
from prettytable import PrettyTable

x = PrettyTable()
```

```
x.field_names = ["Layer ","Test_Score", "Test_Accuracy", "Epoch", "Drop_Outrate","Optimizer","ACtiv
ation","Drop_out + Normalization Layers","Test_performance"]

x.add_row(["2", 0.057, 0.98,20, 0.5,"ADAM",      "ReLu","Every","good"])
x.add_row(["2", 0.10,  0.98,20, 0.5,"ADAM",      "ReLu","None","Not-good"])
x.add_row(["2", 0.062, 0.98,20, 0.2,"Ada_delta","ReLu","Every","Not-good"])
x.add_row(["2", 0.054, 0.98,20, 0.5,"ADAM",      "ReLu","First","Not-good"])
x.add_row(["2", 0.093, 0.98,20, 0.5,"ADAM",      "ReLu","Last","Not-good"])

print(x)

x2 = PrettyTable()

x2.field_names = ["Layer ","Test_Score", "Test_Accuracy", "Epoch", "Drop_Outrate","Optimizer","ACti
vation","Drop_out + Normalization Layers","Test_performance"]

x2.add_row(["3", 0.050, 0.98,20, 0.5,"ADAM",      "ReLu","Every","good"])
x2.add_row(["3", 0.091,  0.98,20, 0.5,"ADAM",      "ReLu","None","Not-good"])
x2.add_row(["3", 0.059, 0.98,20, 0.2,"Ada_delta","ReLu","Every","Not-good"])
x2.add_row(["3", 0.058, 0.98,20, 0.5,"ADAM",      "ReLu","First","Not-good"])
x2.add_row(["3", 0.066, 0.98,20, 0.5,"ADAM",      "ReLu","Last","Not-good"])

print(x2)

x3 = PrettyTable()

x3.field_names = ["Layer ","Test_Score", "Test_Accuracy", "Epoch", "Drop_Outrate","Optimizer","ACti
vation","Drop_out + Normalization Layers","Test_performance"]

x3.add_row(["5", 0.066, 0.98,20, 0.5,"ADAM",      "ReLu","Every","good"])
x3.add_row(["5", 0.088,  0.98,20, 0.5,"ADAM",      "ReLu","None","Not-good"])
x3.add_row(["5", 0.064, 0.98,20, 0.2,"Ada_delta","ReLu","Every","Not-good"])
x3.add_row(["5", 0.085, 0.98,20, 0.5,"ADAM",      "ReLu","First","Not-good"])
x3.add_row(["5", 0.086, 0.98,20, 0.5,"ADAM",      "ReLu","Last","Not-good"])

print(x3)
```

```
+---------+------------+---------------+-------+--------------+-----------+------------+------------
------------------+------------------+
| Layer   | Test_Score | Test_Accuracy | Epoch | Drop_Outrate | Optimizer | ACtivation | Drop_out +
Normalization Layers | Test_performance |
+---------+------------+---------------+-------+--------------+-----------+------------+------------
------------------+------------------+
|    2    |   0.057    |      0.98     |   20  |     0.5      |    ADAM   |    ReLu    |
Every                   |       good       |
|    2    |    0.1     |      0.98     |   20  |     0.5      |    ADAM   |    ReLu    |
None                  |     Not-good     |
|    2    |   0.062    |      0.98     |   20  |     0.2      | Ada_delta |    ReLu    |
Every                   |     Not-good     |
|    2    |   0.054    |      0.98     |   20  |     0.5      |    ADAM   |    ReLu    |
First                   |     Not-good     |
|    2    |   0.093    |      0.98     |   20  |     0.5      |    ADAM   |    ReLu    |
Last                  |     Not-good     |
+---------+------------+---------------+-------+--------------+-----------+------------+------------
------------------+------------------+
+---------+------------+---------------+-------+--------------+-----------+------------+------------
------------------+------------------+
| Layer   | Test_Score | Test_Accuracy | Epoch | Drop_Outrate | Optimizer | ACtivation | Drop_out +
Normalization Layers | Test_performance |
+---------+------------+---------------+-------+--------------+-----------+------------+------------
------------------+------------------+
|    3    |    0.05    |      0.98     |   20  |     0.5      |    ADAM   |    ReLu    |
Every                   |       good       |
|    3    |   0.091    |      0.98     |   20  |     0.5      |    ADAM   |    ReLu    |
None                  |     Not-good     |
|    3    |   0.059    |      0.98     |   20  |     0.2      | Ada_delta |    ReLu    |
Every                   |     Not-good     |
|    3    |   0.058    |      0.98     |   20  |     0.5      |    ADAM   |    ReLu    |
First                   |     Not-good     |
|    3    |   0.066    |      0.98     |   20  |     0.5      |    ADAM   |    ReLu    |
Last                  |     Not-good     |
+---------+------------+---------------+-------+--------------+-----------+------------+------------
------------------+------------------+
+---------+------------+---------------+-------+--------------+-----------+------------+------------
------------------+------------------+
```

Layer	Test_Score	Test_Accuracy	Epoch	Drop_Outrate	Optimizer	ACtivation	Drop_out + Normalization Layers	Test_performance
5	0.066	0.98	20	0.5	ADAM	ReLu	Every	good
5	0.088	0.98	20	0.5	ADAM	ReLu	None	Not-good
5	0.064	0.98	20	0.2	Ada_delta	ReLu	Every	Not-good
5	0.085	0.98	20	0.5	ADAM	ReLu	First	Not-good
5	0.086	0.98	20	0.5	ADAM	ReLu	Last	Not-good

Observations

1. Applied Various Level Architectures(2,3,5) for observing the model performance using MNIST data
2. Applied models with and with out Batch Normalization and Drop_out rate
3. Models with batch normalization and dropuout rate gives better results compare to without apply
4. For all models we get same kind of accuracy but difference occur at test_loss i.e, with-out batch models we got test-loss > train loss leads to bad model performance
5. We use Constant drop out rate, we may get good results with opitmal drop-out rate and optimal layers by doing some hyper parameter tuning for drop-out and no of layers and no of neurons per layers
6. We get similar performance for 2,3,5 architectures with batch normalization and drop-out rate 3 layer architecture gives smoother curve at test loss compare to 2,5 architectures
7. If we observe above tables model with batch-normalization and drop-out 0.5 at every layers model gives good performance
8. If we took low drop-rate and high drop rate with out batch normalization model performance is not good observe the above error plots for every model observe the difference
9. Models with batch-normalization and drop-out rate 0.5 at every layers gives similar performance which is good 3 layer architecture gives good performance because it converges with train loss means training and validation performs well