MLP on MNIST dataset in Keras

Steps to follow in this assignment:-

1. Load libraries and MNIST data
2. Normalize the data
3. Convert class label values to one-hot encoded values
4. Implementing Softmax classifier with 2 , 3 , 5 hidden layers
5. Implementing model with and without dropout and normalization
6. Compiling the model
7. Plotting Categorical Crossentropy Loss VS Epochs plot
8. Plotting Violin plots to check weights distribution

1. Loading libraries

In [0]:
```
from keras.utils import np_utils
from keras.datasets import mnist
import seaborn as sns
from keras.initializers import RandomNormal
```

```
Using TensorFlow backend.
```

2. Loading MNIST data

In [0]:
```
# Loading MNIST Train and Test data
(X_train, y_train), (X_test, y_test) = mnist.load_data()
```

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

In [0]:
```
# Printing to see how many data points are there for train and test and to see
each image size

print("Number of Train data points :", X_train.shape[0], "and each image is of
shape (%d, %d)"%(X_train.shape[1], X_train.shape[2]))
print("Number of Test data points :", X_test.shape[0], "and each image is of s
hape (%d, %d)"%(X_test.shape[1], X_test.shape[2]))
```

```
Number of Train data points : 60000 and each image is of shape (28, 28)
Number of Test data points : 10000 and each image is of shape (28, 28)
```

In [0]:
```
# if you observe the input shape its 3 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
# We are reshaping the train and test data points to 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 [0]:
```
# after converting the input images from 3d to 2d vectors , printing the shape
s of train and test data

print("Number of Train data points after reshape :", X_train.shape[0], "and ea
ch image is of shape (%d)"%(X_train.shape[1]))
print("Number of Test data points after reshape :", X_test.shape[0], "and each
image is of shape (%d)"%(X_test.shape[1]))
```

```
Number of Train data points after reshape : 60000 and each image is of shape
(784)
Number of Test data points after reshape : 10000 and each image is of shape
(784)
```

In [0]:
```
# Printing an example data point

print(X_train[0])
```

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

2.1 Normalizing the data

In [0]:
```
# if we observe the above matrix each cell is having a value between 0-255
# before we move to apply machine learning algorithms lets normalize the data
 so that all values lie between 0 to 1 instead of 0 to 255
# X => (X - Xmin)/(Xmax-Xmin) = X/255 . This is min-max type of normalization

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

In [0]:
```
# printing example train 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.        ]
```

2.2 Converting to One-Hot encoding

In [0]:

```
# Here in this dataset, class labels for each image are numbers (0,1,2,3,...),
so I want to convert them into one-hot encoded vectors

print("Class label of first image :", y_train[0])

# lets convert this into a 10 dimensional vector
# ex: consider an image with class label of 5 and convert it into one-hot enco
ded vector of 0's and 1's - 5 => [0, 0, 0, 0, 0, 1, 0, 0, 0, 0]
# this conversion is needed for MLPs

Y_train = np_utils.to_categorical(y_train, 10)   # using np.utils we can conve
rt numbers into one-hot encoding
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]:
```
# this function is used draw Categorical Crossentropy Loss vs No. of epochs pl
ot
import matplotlib.pyplot as plt
%matplotlib inline
import numpy as np
import time

def plt_dynamic(x, vy, ty):
    plt.figure(figsize=(10,6))
    plt.plot(x, ty, 'b', label="Train Loss")
    plt.plot(x, vy, 'r', label="Validation/Test Loss")
    plt.title('\nCategorical Crossentropy Loss VS Epochs')
    plt.xlabel('Epochs')
    plt.ylabel('Categorical Crossentropy Loss-Train and Test loss')
    plt.legend()
    plt.grid()
    plt.show()
```

3. Softmax Classifier with 2 hidden layers

3.1 Model without dropout and Batch Normalization

In [0]:
```
from keras.models import Sequential
from keras.layers import Dense, Activation
from keras.initializers import he_normal

# some model parameters

output_dim = 10
input_dim = X_train.shape[1] # size of X
batch_size = 128
nb_epoch = 20    # run 20times
```

3.2 Building the model

In [0]:
```
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")

# start building a model
# Initializing the sequential model as the layers are in sequential

model = Sequential()

# Adding first hidden layer
model.add(Dense(364, activation='relu', input_shape=(input_dim,), kernel_initi
alizer=he_normal(seed=None)))

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

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

# Printing model summary
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_4 (Dense)              (None, 364)               285740    
_________________________________________________________________
dense_5 (Dense)              (None, 52)                18980     
_________________________________________________________________
dense_6 (Dense)              (None, 10)                530       
=================================================================
Total params: 305,250
Trainable params: 305,250
Non-trainable params: 0
_________________________________________________________________
```

In [0]:
```
# Compiling the model
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['acc
uracy'])

# Fitting the model
# To fit the model, give input data, batch_size, number of epochs and validati
on/test data

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

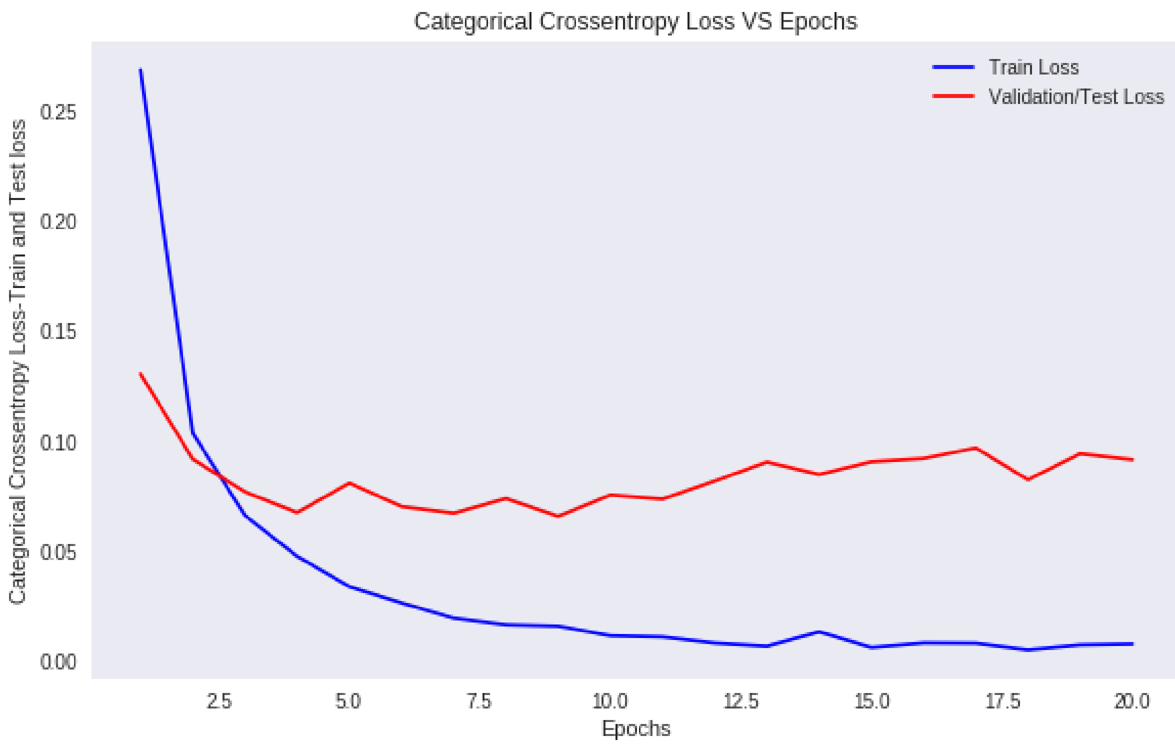
```
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/tensorflow/pyt
hon/ops/math_ops.py:3066: to_int32 (from tensorflow.python.ops.math_ops) is d
eprecated and will be removed in a future version.
Instructions for updating:
Use tf.cast instead.
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 6s 100us/step - loss: 0.2683 -
acc: 0.9218 - val_loss: 0.1305 - val_acc: 0.9612
Epoch 2/20
60000/60000 [==============================] - 5s 87us/step - loss: 0.1036 -
acc: 0.9692 - val_loss: 0.0918 - val_acc: 0.9712
Epoch 3/20
60000/60000 [==============================] - 5s 86us/step - loss: 0.0662 -
acc: 0.9802 - val_loss: 0.0769 - val_acc: 0.9753
Epoch 4/20
60000/60000 [==============================] - 5s 85us/step - loss: 0.0477 -
acc: 0.9854 - val_loss: 0.0676 - val_acc: 0.9787
Epoch 5/20
60000/60000 [==============================] - 5s 86us/step - loss: 0.0340 -
acc: 0.9898 - val_loss: 0.0809 - val_acc: 0.9751
Epoch 6/20
60000/60000 [==============================] - 5s 86us/step - loss: 0.0266 -
acc: 0.9917 - val_loss: 0.0704 - val_acc: 0.9795
Epoch 7/20
60000/60000 [==============================] - 5s 86us/step - loss: 0.0197 -
acc: 0.9946 - val_loss: 0.0673 - val_acc: 0.9802
Epoch 8/20
60000/60000 [==============================] - 5s 86us/step - loss: 0.0167 -
acc: 0.9948 - val_loss: 0.0740 - val_acc: 0.9788
Epoch 9/20
60000/60000 [==============================] - 5s 87us/step - loss: 0.0161 -
acc: 0.9948 - val_loss: 0.0659 - val_acc: 0.9820
Epoch 10/20
60000/60000 [==============================] - 5s 84us/step - loss: 0.0118 -
acc: 0.9960 - val_loss: 0.0756 - val_acc: 0.9806
Epoch 11/20
60000/60000 [==============================] - 5s 82us/step - loss: 0.0112 -
acc: 0.9964 - val_loss: 0.0737 - val_acc: 0.9817
Epoch 12/20
60000/60000 [==============================] - 5s 84us/step - loss: 0.0085 -
acc: 0.9975 - val_loss: 0.0819 - val_acc: 0.9796
Epoch 13/20
60000/60000 [==============================] - 5s 83us/step - loss: 0.0070 -
acc: 0.9980 - val_loss: 0.0904 - val_acc: 0.9778
Epoch 14/20
60000/60000 [==============================] - 5s 83us/step - loss: 0.0135 -
acc: 0.9957 - val_loss: 0.0848 - val_acc: 0.9810
Epoch 15/20
60000/60000 [==============================] - 5s 85us/step - loss: 0.0065 -
acc: 0.9980 - val_loss: 0.0906 - val_acc: 0.9791
Epoch 16/20
60000/60000 [==============================] - 5s 84us/step - loss: 0.0085 -
acc: 0.9970 - val_loss: 0.0921 - val_acc: 0.9782
Epoch 17/20
60000/60000 [==============================] - 5s 81us/step - loss: 0.0084 -
acc: 0.9973 - val_loss: 0.0968 - val_acc: 0.9791
```

```
Epoch 18/20
60000/60000 [==============================] - 5s 84us/step - loss: 0.0054 -
acc: 0.9982 - val_loss: 0.0825 - val_acc: 0.9827
Epoch 19/20
60000/60000 [==============================] - 5s 85us/step - loss: 0.0076 -
acc: 0.9975 - val_loss: 0.0943 - val_acc: 0.9803
Epoch 20/20
60000/60000 [==============================] - 5s 89us/step - loss: 0.0080 -
acc: 0.9974 - val_loss: 0.0915 - val_acc: 0.9820
```

3.3 Plotting the model values

In [0]:
```
# Evaluating the model on test data
score = model.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

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

# we will get val_loss and val_acc only when you pass the paramter validation_data
# val_loss : validation loss
vy = history.history['val_loss']

# Training loss
ty = history.history['loss']
# calling the dynamic function to draw the plot
plt_dynamic(x, vy, ty)
```

```
Test score: 0.09153629648885012
Test accuracy: 0.982
```



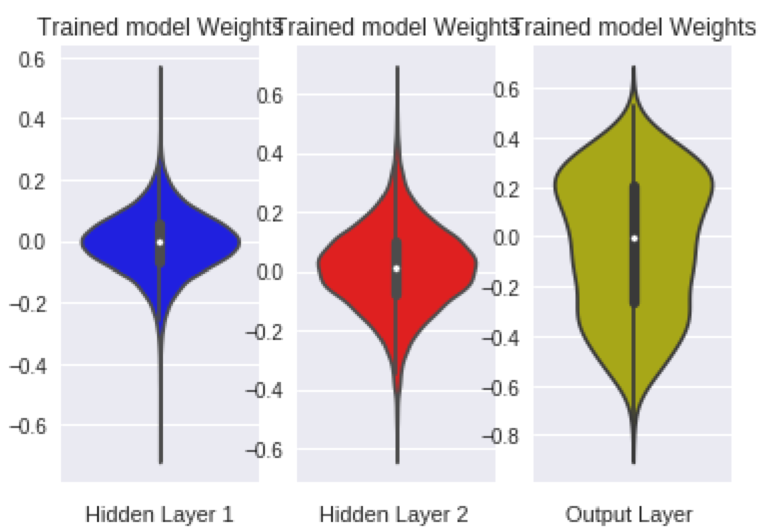
Observations:-

1. In this plot, as we are running more epochs the train and test loss are reducing , but test loss started increasing after epoch 9 and train loss/error is reducing further. This leads to model overfitting
2. Actually test loss should decrease, but in above plot its increasing and both train and test loss are diverging which leads to overfitting of model.
3. To avoid this, we can add regularizations like dropouts.

3.4 Plotting Violin plots of hidden and output layers to see weights distribution

This is like sanity check. This is needed to make sure that weights are not too large or too small.

In [0]:
```
w_after = model.get_weights()

# weights of hidden layer 1
h1_w = w_after[0].flatten().reshape(-1,1)
# weights of hidden layer 2
h2_w = w_after[2].flatten().reshape(-1,1)
# weights of output layer
out_w = w_after[4].flatten().reshape(-1,1)

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

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

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



Observation:-

1. For the hidden layers, I got good gaussian structures and weights are nicely distributed . For output layer it is like combination of 2 gaussian structures .
2. All the weights are centered around 0 and have reasonable variance and all are working well.

3.5 Model with dropout and Batch Normalization

In [0]:
```
from keras.layers.normalization import BatchNormalization
from keras.layers import Dropout
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")

model_drop = Sequential()

# First hidden layer
model_drop.add(Dense(364, activation='relu', input_shape=(input_dim,), kernel_
initializer=he_normal(seed=None)))
# Adding Batch Normalization
model_drop.add(BatchNormalization())
# Adding Dropout
model_drop.add(Dropout(0.5))

# Second hidden layer
model_drop.add(Dense(52, activation='relu', kernel_initializer=he_normal(seed=
None)))
# Adding Batch Normalization
model_drop.add(BatchNormalization())
# Adding Dropout
model_drop.add(Dropout(0.5))

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


model_drop.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_10 (Dense)             (None, 364)               285740    
_________________________________________________________________
batch_normalization_3 (Batch (None, 364)               1456      
_________________________________________________________________
dropout_3 (Dropout)          (None, 364)               0         
_________________________________________________________________
dense_11 (Dense)             (None, 52)                18980     
_________________________________________________________________
batch_normalization_4 (Batch (None, 52)                208       
_________________________________________________________________
dropout_4 (Dropout)          (None, 52)                0         
_________________________________________________________________
dense_12 (Dense)             (None, 10)                530       
=================================================================
Total params: 306,914
Trainable params: 306,082
Non-trainable params: 832
_________________________________________________________________
```

In [0]:
```
# Compiling the model
model_drop.compile(optimizer='adam', loss='categorical_crossentropy', metrics=
['accuracy'])

# Fitting the model

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

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 7s 119us/step - loss: 0.5380 -
acc: 0.8405 - val_loss: 0.1708 - val_acc: 0.9485
Epoch 2/20
60000/60000 [==============================] - 6s 104us/step - loss: 0.2567 -
acc: 0.9259 - val_loss: 0.1255 - val_acc: 0.9603
Epoch 3/20
60000/60000 [==============================] - 6s 104us/step - loss: 0.1998 -
acc: 0.9431 - val_loss: 0.1044 - val_acc: 0.9678
Epoch 4/20
60000/60000 [==============================] - 6s 105us/step - loss: 0.1731 -
acc: 0.9509 - val_loss: 0.0930 - val_acc: 0.9717
Epoch 5/20
60000/60000 [==============================] - 6s 108us/step - loss: 0.1526 -
acc: 0.9566 - val_loss: 0.0822 - val_acc: 0.9737
Epoch 6/20
60000/60000 [==============================] - 6s 106us/step - loss: 0.1421 -
acc: 0.9596 - val_loss: 0.0838 - val_acc: 0.9728
Epoch 7/20
60000/60000 [==============================] - 6s 102us/step - loss: 0.1304 -
acc: 0.9622 - val_loss: 0.0783 - val_acc: 0.9771
Epoch 8/20
60000/60000 [==============================] - 6s 101us/step - loss: 0.1237 -
acc: 0.9643 - val_loss: 0.0726 - val_acc: 0.9787
Epoch 9/20
60000/60000 [==============================] - 6s 104us/step - loss: 0.1119 -
acc: 0.9673 - val_loss: 0.0741 - val_acc: 0.9793
Epoch 10/20
60000/60000 [==============================] - 6s 103us/step - loss: 0.1073 -
acc: 0.9679 - val_loss: 0.0728 - val_acc: 0.9804
Epoch 11/20
60000/60000 [==============================] - 6s 104us/step - loss: 0.1046 -
acc: 0.9693 - val_loss: 0.0637 - val_acc: 0.9809
Epoch 12/20
60000/60000 [==============================] - 6s 105us/step - loss: 0.0956 -
acc: 0.9715 - val_loss: 0.0711 - val_acc: 0.9797
Epoch 13/20
60000/60000 [==============================] - 6s 107us/step - loss: 0.0924 -
acc: 0.9732 - val_loss: 0.0671 - val_acc: 0.9805
Epoch 14/20
60000/60000 [==============================] - 6s 107us/step - loss: 0.0918 -
acc: 0.9728 - val_loss: 0.0699 - val_acc: 0.9800
Epoch 15/20
60000/60000 [==============================] - 6s 108us/step - loss: 0.0883 -
acc: 0.9738 - val_loss: 0.0667 - val_acc: 0.9812
Epoch 16/20
60000/60000 [==============================] - 6s 108us/step - loss: 0.0851 -
acc: 0.9752 - val_loss: 0.0667 - val_acc: 0.9807
Epoch 17/20
60000/60000 [==============================] - 6s 105us/step - loss: 0.0802 -
acc: 0.9756 - val_loss: 0.0624 - val_acc: 0.9816
Epoch 18/20
60000/60000 [==============================] - 6s 104us/step - loss: 0.0817 -
acc: 0.9755 - val_loss: 0.0622 - val_acc: 0.9821
Epoch 19/20
60000/60000 [==============================] - 7s 111us/step - loss: 0.0746 -
```

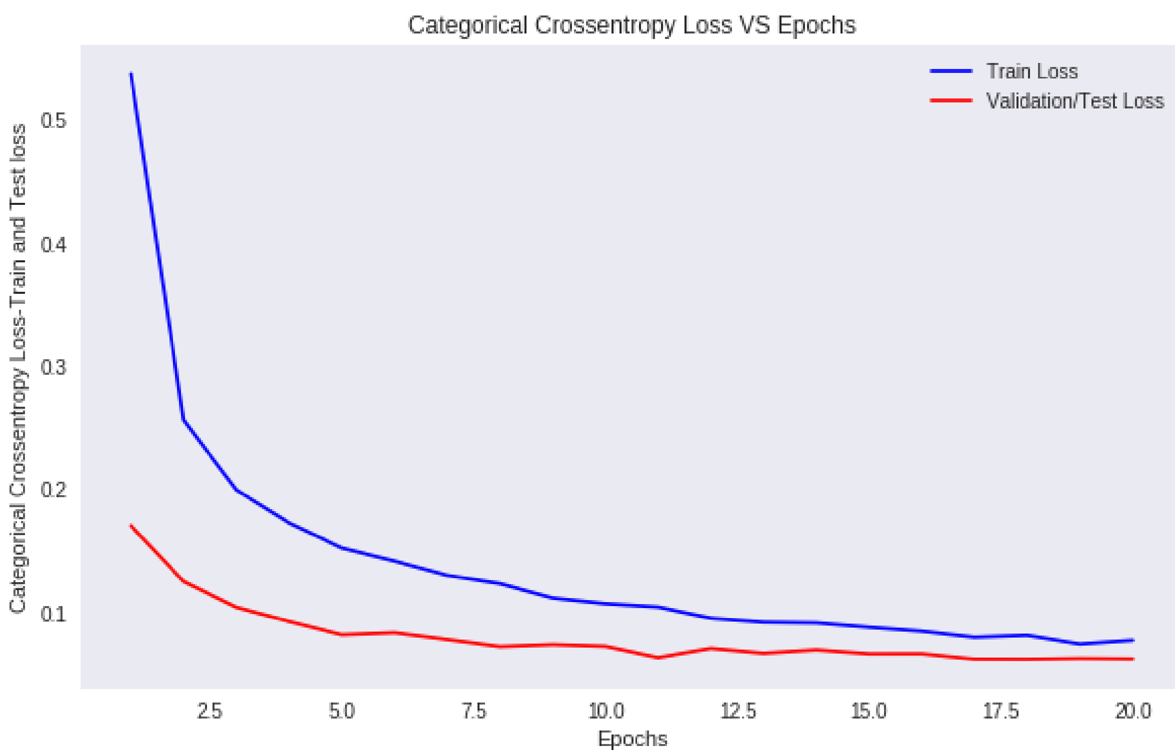
```
acc: 0.9779 - val_loss: 0.0629 - val_acc: 0.9823
Epoch 20/20
60000/60000 [==============================] - 7s 110us/step - loss: 0.0776 -
acc: 0.9774 - val_loss: 0.0625 - val_acc: 0.9818
```

3.6 Plotting the model values

In [0]:

```
# Evaluating the model on test data
score_drop = model_drop.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score_drop[0])
print('Test accuracy:', score_drop[1])

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

# we will get val_loss and val_acc only when you pass the paramter validation_
data
# val_loss : validation loss
vy = history.history['val_loss']

# Training loss
ty = history.history['loss']
# calling the dynamic function to draw the plot
plt_dynamic(x, vy, ty)
```

```
Test score: 0.062534334171749652
Test accuracy: 0.9818
```

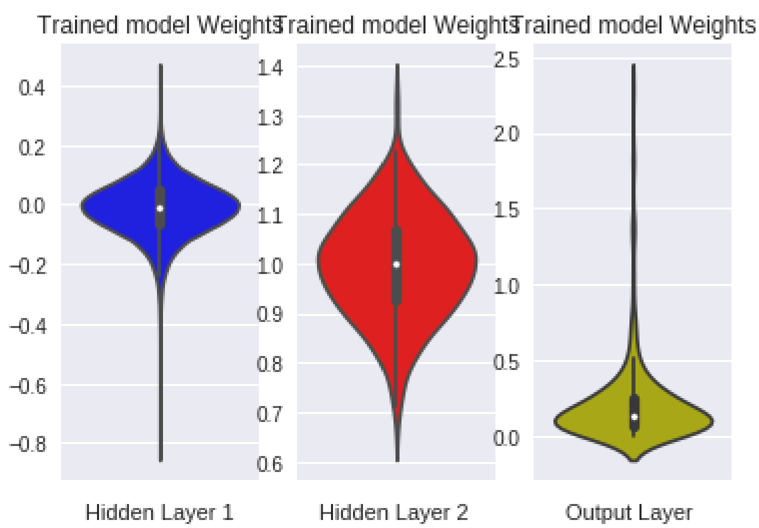


Observation:-

1. After adding dropout, both Train and Test loss are significantly reducing and there is no divergence / increasing between them .

3.7 Plotting Violin plots of hidden and output layers to see weights distribution

In [0]:
```
w_after = model_drop.get_weights()

# weights of hidden layer 1
h1_w = w_after[0].flatten().reshape(-1,1)
# weights of hidden layer 2
h2_w = w_after[2].flatten().reshape(-1,1)
# weights of output layer
out_w = w_after[4].flatten().reshape(-1,1)

fig = plt.figure()
plt.title("Weight matrices after model trained\n")

# Hidden Layer 1
plt.subplot(1, 3, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

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

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



4. Softmax Classifier with 3 hidden layers

4.1 Model without dropout and Batch Normalization

In [0]:
```
# start building a model with 3 hidden layers
# Initializing the sequential model as the layers are in sequential
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")

model_1 = Sequential()

# Adding first hidden layer
model_1.add(Dense(420, activation='relu', input_shape=(input_dim,), kernel_ini
tializer=he_normal(seed=None)))

# Adding second hidden layer
model_1.add(Dense(252, activation='relu', kernel_initializer=he_normal(seed=No
ne)))

# Adding third hidden layer
model_1.add(Dense(45, activation='relu', kernel_initializer=he_normal(seed=Non
e)))

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

# Printing model summary
model_1.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_13 (Dense)             (None, 420)               329700    
_________________________________________________________________
dense_14 (Dense)             (None, 252)               106092    
_________________________________________________________________
dense_15 (Dense)             (None, 45)                11385     
_________________________________________________________________
dense_16 (Dense)             (None, 10)                460       
=================================================================
Total params: 447,637
Trainable params: 447,637
Non-trainable params: 0
_________________________________________________________________
```

In [0]:
```
# Compiling the model
model_1.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['a
ccuracy'])

# Fitting the model
# To fit the model, give input data, batch_size, number of epochs and validati
on/test data

history = model_1.fit(X_train, Y_train, batch_size = batch_size, epochs = nb_e
poch, verbose=1, validation_data = (X_test, Y_test))
```

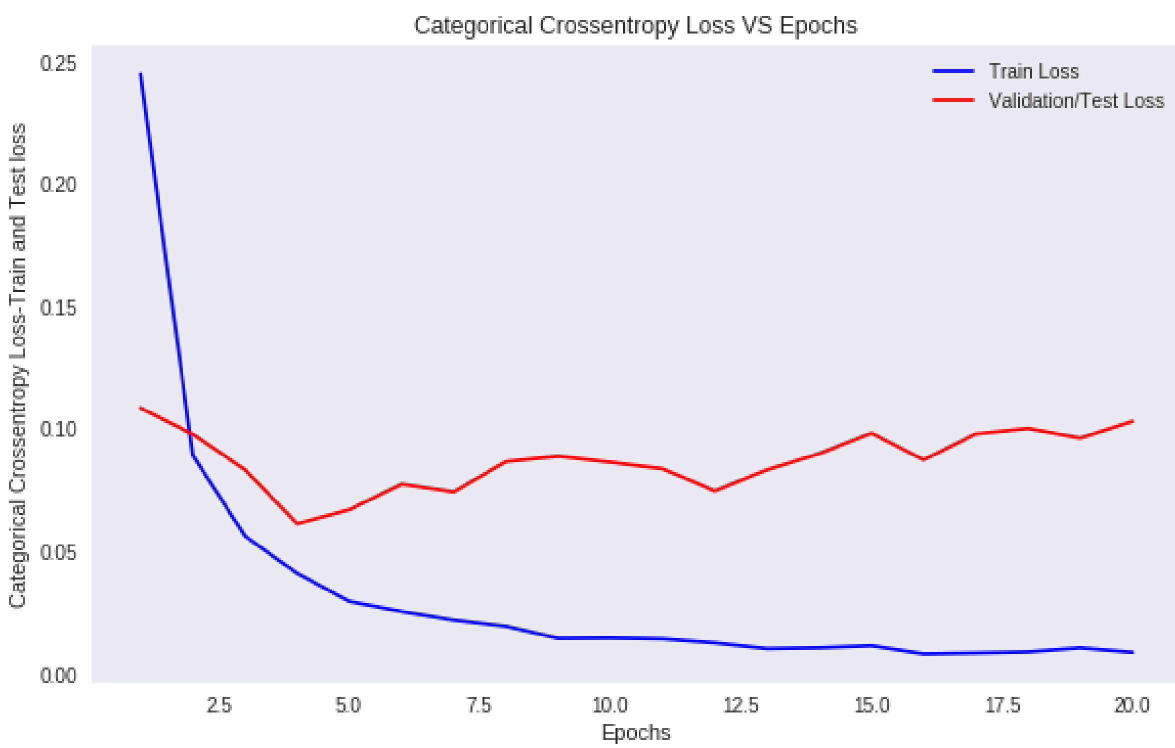
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 8s 127us/step - loss: 0.2451 -
acc: 0.9260 - val_loss: 0.1085 - val_acc: 0.9651
Epoch 2/20
60000/60000 [==============================] - 7s 118us/step - loss: 0.0893 -
acc: 0.9726 - val_loss: 0.0978 - val_acc: 0.9687
Epoch 3/20
60000/60000 [==============================] - 7s 119us/step - loss: 0.0562 -
acc: 0.9829 - val_loss: 0.0833 - val_acc: 0.9749
Epoch 4/20
60000/60000 [==============================] - 7s 119us/step - loss: 0.0410 -
acc: 0.9870 - val_loss: 0.0613 - val_acc: 0.9819
Epoch 5/20
60000/60000 [==============================] - 7s 117us/step - loss: 0.0295 -
acc: 0.9902 - val_loss: 0.0670 - val_acc: 0.9798
Epoch 6/20
60000/60000 [==============================] - 7s 118us/step - loss: 0.0254 -
acc: 0.9916 - val_loss: 0.0775 - val_acc: 0.9782
Epoch 7/20
60000/60000 [==============================] - 7s 115us/step - loss: 0.0219 -
acc: 0.9926 - val_loss: 0.0743 - val_acc: 0.9794
Epoch 8/20
60000/60000 [==============================] - 7s 116us/step - loss: 0.0193 -
acc: 0.9938 - val_loss: 0.0867 - val_acc: 0.9770
Epoch 9/20
60000/60000 [==============================] - 7s 119us/step - loss: 0.0144 -
acc: 0.9949 - val_loss: 0.0889 - val_acc: 0.9792
Epoch 10/20
60000/60000 [==============================] - 7s 118us/step - loss: 0.0146 -
acc: 0.9948 - val_loss: 0.0864 - val_acc: 0.9780
Epoch 11/20
60000/60000 [==============================] - 7s 118us/step - loss: 0.0142 -
acc: 0.9952 - val_loss: 0.0838 - val_acc: 0.9798
Epoch 12/20
60000/60000 [==============================] - 7s 118us/step - loss: 0.0126 -
acc: 0.9959 - val_loss: 0.0747 - val_acc: 0.9818
Epoch 13/20
60000/60000 [==============================] - 7s 118us/step - loss: 0.0103 -
acc: 0.9966 - val_loss: 0.0833 - val_acc: 0.9801
Epoch 14/20
60000/60000 [==============================] - 7s 119us/step - loss: 0.0106 -
acc: 0.9960 - val_loss: 0.0899 - val_acc: 0.9806
Epoch 15/20
60000/60000 [==============================] - 7s 118us/step - loss: 0.0115 -
acc: 0.9963 - val_loss: 0.0983 - val_acc: 0.9788
Epoch 16/20
60000/60000 [==============================] - 7s 116us/step - loss: 0.0081 -
acc: 0.9975 - val_loss: 0.0873 - val_acc: 0.9803
Epoch 17/20
60000/60000 [==============================] - 7s 114us/step - loss: 0.0085 -
acc: 0.9974 - val_loss: 0.0980 - val_acc: 0.9797
Epoch 18/20
60000/60000 [==============================] - 7s 115us/step - loss: 0.0089 -
acc: 0.9971 - val_loss: 0.1002 - val_acc: 0.9792
Epoch 19/20
60000/60000 [==============================] - 7s 118us/step - loss: 0.0106 -
```

```
acc: 0.9966 - val_loss: 0.0963 - val_acc: 0.9818
Epoch 20/20
60000/60000 [==============================] - 7s 116us/step - loss: 0.0088 -
acc: 0.9972 - val_loss: 0.1031 - val_acc: 0.9807
```

4.2 Plotting the model values

In [0]:
```
# Evaluating the model on test data
score_1 = model_1.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score_1[0])
print('Test accuracy:', score_1[1])

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

# https://machinelearningmastery.com/display-deep-learning-model-training-hist
ory-in-keras/
# we will get val_loss and val_acc only when you pass the paramter validation_
data
# for each key in histrory.histrory we will have a list of length equal to num
ber of epochs. History records training metrics for each epoch.
# This includes the loss and the accuracy as well as the loss and accuracy for
the validation dataset, if one is set.
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])

# val_loss : validation loss
vy = history.history['val_loss']
# Training loss
ty = history.history['loss']

# calling the dynamic function to draw the plot
plt_dynamic(x, vy, ty)
```

```
Test score: 0.10307921019351929
Test accuracy: 0.9807
```

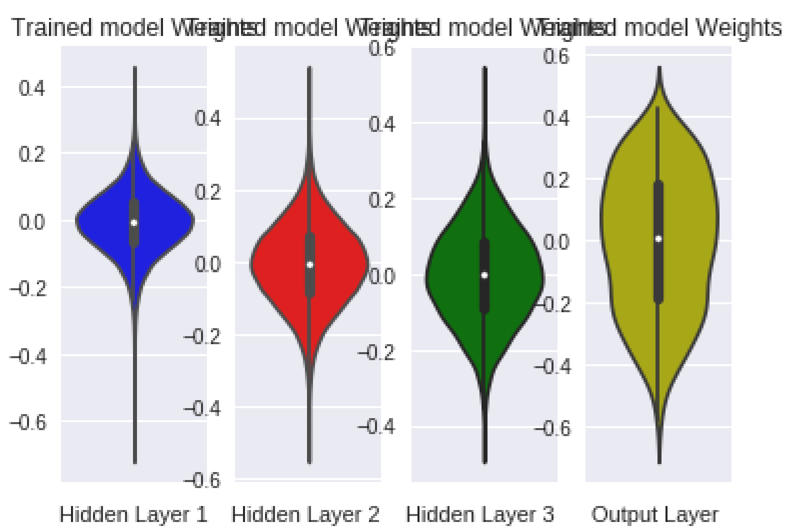


Observations:-

1. In this plot, as we are running more epochs the train and test loss are reducing , but test loss started increasing after epoch 6 and train loss/error is reducing further. This leads to model overfitting
2. Actually test loss should decrease, but in above plot its increasing and both train and test loss are diverging which leads to overfitting of model.
3. To avoid this, we can add regularizations like dropouts.

4.3 Plotting Violin plots of hidden and output layers to see weights distribution

In [0]:
```
w_after = model_1.get_weights()

# 3 hidden layers and output layer
h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
h3_w = w_after[4].flatten().reshape(-1,1)
out_w = w_after[6].flatten().reshape(-1,1)

fig = plt.figure()
plt.title("Weight matrices after model trained\n")

# For hidden layer 1
plt.subplot(1, 4, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

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

#For hidden layer 3
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()
```



4.4 Model with dropout and Batch Normalization

In [0]:
```
from keras.layers.normalization import BatchNormalization
from keras.layers import Dropout
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")

model_1_drop = Sequential()

# First hidden layer
model_1_drop.add(Dense(420, activation='relu', input_shape=(input_dim,), kerne
l_initializer=he_normal(seed=None)))
# Adding Batch Normalization
model_1_drop.add(BatchNormalization())
# Adding Dropout
model_1_drop.add(Dropout(0.5))

# Second hidden layer
model_1_drop.add(Dense(252, activation='relu', kernel_initializer=he_normal(se
ed=None)))
# Adding Batch Normalization
model_1_drop.add(BatchNormalization())
# Adding Dropout
model_1_drop.add(Dropout(0.5))

# Third hidden layer
model_1_drop.add(Dense(45, activation='relu', kernel_initializer=he_normal(see
d=None)))
# Adding Batch Normalization
model_1_drop.add(BatchNormalization())
# Adding Dropout
model_1_drop.add(Dropout(0.5))

# Output layer
model_1_drop.add(Dense(output_dim, activation='softmax'))


model_1_drop.summary()
```

```
Layer (type)                 Output Shape              Param #
=================================================================
dense_17 (Dense)             (None, 420)               329700
_________________________________________________________________
batch_normalization_5 (Batch (None, 420)               1680
_________________________________________________________________
dropout_5 (Dropout)          (None, 420)               0
_________________________________________________________________
dense_18 (Dense)             (None, 252)               106092
_________________________________________________________________
batch_normalization_6 (Batch (None, 252)               1008
_________________________________________________________________
dropout_6 (Dropout)          (None, 252)               0
_________________________________________________________________
dense_19 (Dense)             (None, 45)                11385
_________________________________________________________________
batch_normalization_7 (Batch (None, 45)                180
_________________________________________________________________
dropout_7 (Dropout)          (None, 45)                0
_________________________________________________________________
dense_20 (Dense)             (None, 10)                460
=================================================================
Total params: 450,505
Trainable params: 449,071
Non-trainable params: 1,434
_________________________________________________________________
```

In [0]:
```
# Compiling the model
model_1_drop.compile(optimizer='adam', loss='categorical_crossentropy', metric
s=['accuracy'])

# Fitting the model

history = model_1_drop.fit(X_train, Y_train, batch_size = batch_size, epochs =
nb_epoch, verbose=1, validation_data = (X_test, Y_test))
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 11s 181us/step - loss: 0.6888
- acc: 0.7916 - val_loss: 0.1892 - val_acc: 0.9412
Epoch 2/20
60000/60000 [==============================] - 10s 160us/step - loss: 0.2975
- acc: 0.9179 - val_loss: 0.1274 - val_acc: 0.9596
Epoch 3/20
60000/60000 [==============================] - 9s 158us/step - loss: 0.2302 -
acc: 0.9372 - val_loss: 0.1156 - val_acc: 0.9645
Epoch 4/20
60000/60000 [==============================] - 9s 158us/step - loss: 0.1955 -
acc: 0.9456 - val_loss: 0.0927 - val_acc: 0.9728
Epoch 5/20
60000/60000 [==============================] - 9s 157us/step - loss: 0.1660 -
acc: 0.9546 - val_loss: 0.0977 - val_acc: 0.9714
Epoch 6/20
60000/60000 [==============================] - 10s 158us/step - loss: 0.1559
- acc: 0.9566 - val_loss: 0.0861 - val_acc: 0.9738
Epoch 7/20
60000/60000 [==============================] - 10s 159us/step - loss: 0.1418
- acc: 0.9600 - val_loss: 0.0807 - val_acc: 0.9765
Epoch 8/20
60000/60000 [==============================] - 10s 159us/step - loss: 0.1333
- acc: 0.9637 - val_loss: 0.0731 - val_acc: 0.9785
Epoch 9/20
60000/60000 [==============================] - 9s 156us/step - loss: 0.1274 -
acc: 0.9652 - val_loss: 0.0800 - val_acc: 0.9779
Epoch 10/20
60000/60000 [==============================] - 9s 156us/step - loss: 0.1168 -
acc: 0.9673 - val_loss: 0.0784 - val_acc: 0.9777
Epoch 11/20
60000/60000 [==============================] - 9s 156us/step - loss: 0.1105 -
acc: 0.9688 - val_loss: 0.0695 - val_acc: 0.9787
Epoch 12/20
60000/60000 [==============================] - 9s 156us/step - loss: 0.1045 -
acc: 0.9703 - val_loss: 0.0732 - val_acc: 0.9795
Epoch 13/20
60000/60000 [==============================] - 9s 157us/step - loss: 0.1041 -
acc: 0.9709 - val_loss: 0.0678 - val_acc: 0.9806
Epoch 14/20
60000/60000 [==============================] - 10s 159us/step - loss: 0.0973
- acc: 0.9723 - val_loss: 0.0706 - val_acc: 0.9805
Epoch 15/20
60000/60000 [==============================] - 10s 159us/step - loss: 0.0959
- acc: 0.9742 - val_loss: 0.0664 - val_acc: 0.9816
Epoch 16/20
60000/60000 [==============================] - 10s 159us/step - loss: 0.0902
- acc: 0.9739 - val_loss: 0.0658 - val_acc: 0.9822
Epoch 17/20
60000/60000 [==============================] - 9s 158us/step - loss: 0.0853 -
acc: 0.9755 - val_loss: 0.0657 - val_acc: 0.9832
Epoch 18/20
60000/60000 [==============================] - 9s 157us/step - loss: 0.0838 -
acc: 0.9759 - val_loss: 0.0655 - val_acc: 0.9819
Epoch 19/20
60000/60000 [==============================] - 9s 156us/step - loss: 0.0827 -
```

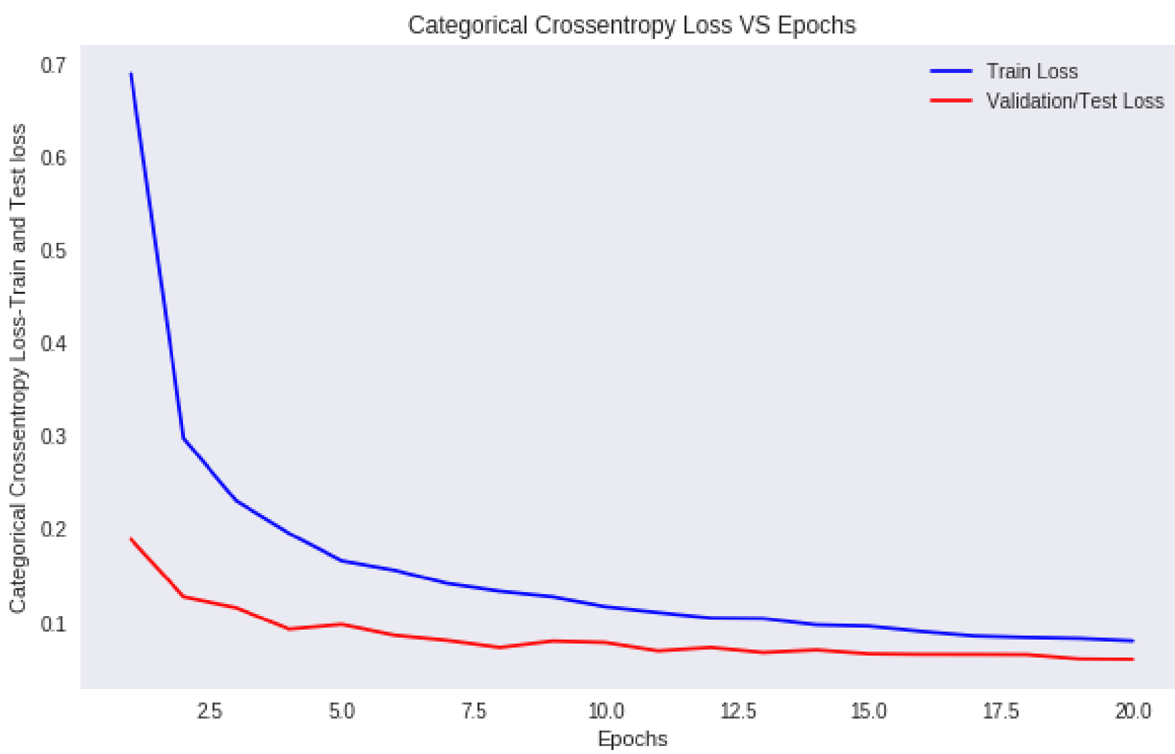
```
acc: 0.9771 - val_loss: 0.0608 - val_acc: 0.9839
Epoch 20/20
60000/60000 [==============================] - 9s 153us/step - loss: 0.0801 -
acc: 0.9774 - val_loss: 0.0603 - val_acc: 0.9834
```

4.5 Plotting the model values

In [0]:

```
# Evaluating the model on test data
score_1_drop = model_1_drop.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score_1_drop[0])
print('Test accuracy:', score_1_drop[1])

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

# we will get val_loss and val_acc only when you pass the paramter validation_
data
# val_loss : validation loss
vy = history.history['val_loss']

# Training loss
ty = history.history['loss']
# calling the dynamic function to draw the plot
plt_dynamic(x, vy, ty)
```

```
Test score: 0.06033782551859O4
Test accuracy: 0.9834
```

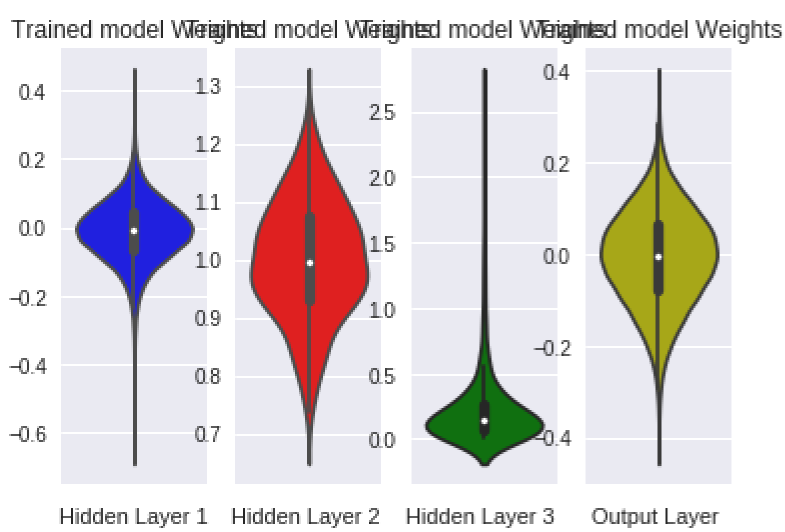


Observation:-

After adding dropout, both Train and Test loss are significantly reducing /converging and there is no divergence / increasing between them .

4.6 Plotting Violin plots of hidden and output layers to see weights distribution

In [0]:
```
w_after = model_1_drop.get_weights()

# weights of hidden layer 1
h1_w = w_after[0].flatten().reshape(-1,1)
# weights of hidden layer 2
h2_w = w_after[2].flatten().reshape(-1,1)
# weights of hidden layer 3
h3_w = w_after[4].flatten().reshape(-1,1)
# weights of output layer
out_w = w_after[6].flatten().reshape(-1,1)

# Plotting the violin plots
fig = plt.figure()
plt.title("Weight matrices after model trained\n")

# Hidden layer 1
plt.subplot(1, 4, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

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

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


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



5. Softmax Classifier with 5 hidden layers

5.1 Model without dropout and Batch Normalization

In [0]:
```
# start building a model with 5 hidden layers
# Initializing the sequential model as the layers are in sequential
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")

model_2 = Sequential()

# Adding first hidden layer
model_2.add(Dense(532, activation='relu', input_shape=(input_dim,), kernel_ini
tializer=he_normal(seed=None)))

# Adding second hidden layer
model_2.add(Dense(354, activation='relu', kernel_initializer=he_normal(seed=No
ne)))

# Adding third hidden layer
model_2.add(Dense(165, activation='relu', kernel_initializer=he_normal(seed=No
ne)))

# Adding fourth hidden layer
model_2.add(Dense(83, activation='relu', kernel_initializer=he_normal(seed=Non
e)))

# Adding fifth hidden layer
model_2.add(Dense(34, activation='relu', kernel_initializer=he_normal(seed=Non
e)))

# Adding output layer
model_2.add(Dense(output_dim, activation='softmax'))

# Printing model summary
model_2.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_21 (Dense)             (None, 532)               417620    
_________________________________________________________________
dense_22 (Dense)             (None, 354)               188682    
_________________________________________________________________
dense_23 (Dense)             (None, 165)               58575     
_________________________________________________________________
dense_24 (Dense)             (None, 83)                13778     
_________________________________________________________________
dense_25 (Dense)             (None, 34)                2856      
_________________________________________________________________
dense_26 (Dense)             (None, 10)                350       
=================================================================
Total params: 681,861
Trainable params: 681,861
Non-trainable params: 0
_________________________________________________________________
```

In [0]:
```
# Compiling the model
model_2.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['a
ccuracy'])

# Fitting the model
# To fit the model, give input data, batch_size, number of epochs and validati
on/test data

history = model_2.fit(X_train, Y_train, batch_size = batch_size, epochs = nb_e
poch, verbose=1, validation_data = (X_test, Y_test))
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 12s 192us/step - loss: 0.2578
- acc: 0.9197 - val_loss: 0.1270 - val_acc: 0.9578
Epoch 2/20
60000/60000 [==============================] - 10s 170us/step - loss: 0.0911
- acc: 0.9718 - val_loss: 0.0933 - val_acc: 0.9718
Epoch 3/20
60000/60000 [==============================] - 10s 173us/step - loss: 0.0614
- acc: 0.9804 - val_loss: 0.0871 - val_acc: 0.9730
Epoch 4/20
60000/60000 [==============================] - 10s 171us/step - loss: 0.0464
- acc: 0.9846 - val_loss: 0.0854 - val_acc: 0.9757
Epoch 5/20
60000/60000 [==============================] - 10s 171us/step - loss: 0.0380
- acc: 0.9879 - val_loss: 0.0770 - val_acc: 0.9785
Epoch 6/20
60000/60000 [==============================] - 10s 171us/step - loss: 0.0292
- acc: 0.9905 - val_loss: 0.0789 - val_acc: 0.9766
Epoch 7/20
60000/60000 [==============================] - 10s 172us/step - loss: 0.0293
- acc: 0.9906 - val_loss: 0.0700 - val_acc: 0.9821
Epoch 8/20
60000/60000 [==============================] - 11s 176us/step - loss: 0.0253
- acc: 0.9919 - val_loss: 0.0860 - val_acc: 0.9797
Epoch 9/20
60000/60000 [==============================] - 10s 174us/step - loss: 0.0221
- acc: 0.9925 - val_loss: 0.0784 - val_acc: 0.9811
Epoch 10/20
60000/60000 [==============================] - 10s 172us/step - loss: 0.0181
- acc: 0.9938 - val_loss: 0.0826 - val_acc: 0.9796
Epoch 11/20
60000/60000 [==============================] - 10s 173us/step - loss: 0.0163
- acc: 0.9950 - val_loss: 0.0972 - val_acc: 0.9775
Epoch 12/20
60000/60000 [==============================] - 10s 172us/step - loss: 0.0161
- acc: 0.9948 - val_loss: 0.0794 - val_acc: 0.9800
Epoch 13/20
60000/60000 [==============================] - 10s 173us/step - loss: 0.0148
- acc: 0.9952 - val_loss: 0.0783 - val_acc: 0.9834
Epoch 14/20
60000/60000 [==============================] - 10s 171us/step - loss: 0.0163
- acc: 0.9950 - val_loss: 0.0939 - val_acc: 0.9808
Epoch 15/20
60000/60000 [==============================] - 10s 171us/step - loss: 0.0121
- acc: 0.9964 - val_loss: 0.0874 - val_acc: 0.9799
Epoch 16/20
60000/60000 [==============================] - 10s 171us/step - loss: 0.0130
- acc: 0.9962 - val_loss: 0.0859 - val_acc: 0.9809
Epoch 17/20
60000/60000 [==============================] - 10s 169us/step - loss: 0.0114
- acc: 0.9969 - val_loss: 0.0865 - val_acc: 0.9824
Epoch 18/20
60000/60000 [==============================] - 10s 170us/step - loss: 0.0129
- acc: 0.9962 - val_loss: 0.0752 - val_acc: 0.9836
Epoch 19/20
60000/60000 [==============================] - 10s 170us/step - loss: 0.0106
```

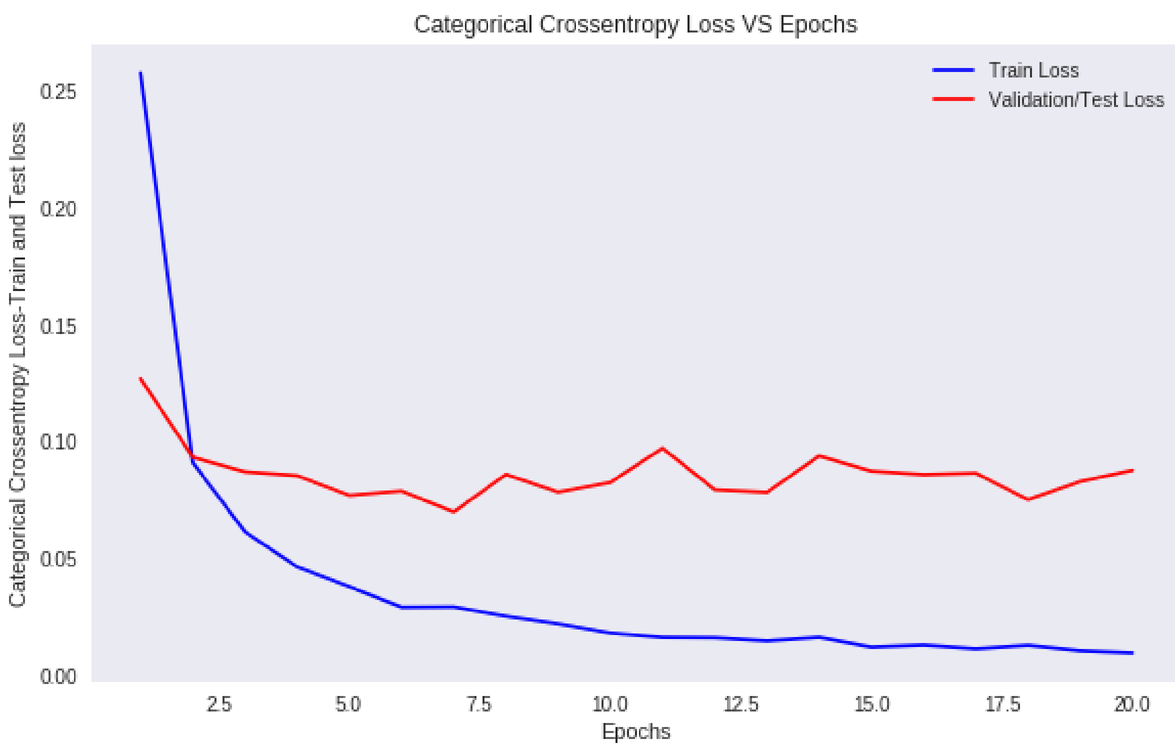
```
- acc: 0.9968 - val_loss: 0.0830 - val_acc: 0.9820
Epoch 20/20
60000/60000 [==============================] - 10s 173us/step - loss: 0.0097
- acc: 0.9970 - val_loss: 0.0877 - val_acc: 0.9824
```

5.2 Plotting the model values

In [0]:

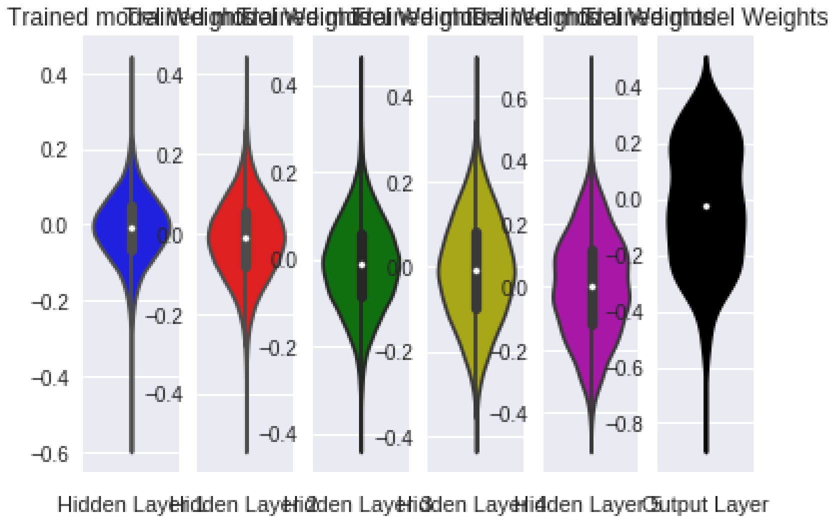
```
# Evaluating the model on test data
score_2 = model_2.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score_2[0])
print('Test accuracy:', score_2[1])

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

# we will get val_loss and val_acc only when you pass the paramter validation_
data
# val_loss : validation loss
vy = history.history['val_loss']

# Training loss
ty = history.history['loss']
# calling the dynamic function to draw the plot
plt_dynamic(x, vy, ty)
```

```
Test score: 0.08769175834859744
Test accuracy: 0.9824
```



5.3 Plotting Violin plots of hidden and output layers to see weights distribution

In [0]:
```
w_after = model_2.get_weights()

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

out_w = w_after[10].flatten().reshape(-1,1)


fig = plt.figure()
plt.title("Weight matrices after model trained\n")

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

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

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

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

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

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



5.4 Model with dropout and Batch Normalization

In [0]:
```
from keras.layers.normalization import BatchNormalization
from keras.layers import Dropout
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")

model_2_drop = Sequential()

# First hidden Layer
model_2_drop.add(Dense(532, activation='relu', input_shape=(input_dim,), kerne
l_initializer=he_normal(seed=None)))
# Adding Batch Normalization
model_2_drop.add(BatchNormalization())
# Adding Dropout
model_2_drop.add(Dropout(0.5))

# Second hidden Layer
model_2_drop.add(Dense(354, activation='relu', kernel_initializer=he_normal(se
ed=None)))
# Adding Batch Normalization
model_2_drop.add(BatchNormalization())
# Adding Dropout
model_2_drop.add(Dropout(0.5))

# Third hidden Layer
model_2_drop.add(Dense(165, activation='relu', kernel_initializer=he_normal(se
ed=None)))
# Adding Batch Normalization
model_2_drop.add(BatchNormalization())
# Adding Dropout
model_2_drop.add(Dropout(0.5))

# Fouth hidden Layer
model_2_drop.add(Dense(83, activation='relu', kernel_initializer=he_normal(see
d=None)))
# Adding Batch Normalization
model_2_drop.add(BatchNormalization())
# Adding Dropout
model_2_drop.add(Dropout(0.5))

# Fifth hidden Layer
model_2_drop.add(Dense(34, activation='relu', kernel_initializer=he_normal(see
d=None)))
# Adding Batch Normalization
model_2_drop.add(BatchNormalization())
# Adding Dropout
model_2_drop.add(Dropout(0.5))

# Output Layer
model_2_drop.add(Dense(output_dim, activation='softmax'))


model_2_drop.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_27 (Dense)             (None, 532)               417620    
_________________________________________________________________
batch_normalization_8 (Batch (None, 532)               2128      
_________________________________________________________________
dropout_8 (Dropout)          (None, 532)               0         
_________________________________________________________________
dense_28 (Dense)             (None, 354)               188682    
_________________________________________________________________
batch_normalization_9 (Batch (None, 354)               1416      
_________________________________________________________________
dropout_9 (Dropout)          (None, 354)               0         
_________________________________________________________________
dense_29 (Dense)             (None, 165)               58575     
_________________________________________________________________
batch_normalization_10 (Batc (None, 165)               660       
_________________________________________________________________
dropout_10 (Dropout)         (None, 165)               0         
_________________________________________________________________
dense_30 (Dense)             (None, 83)                13778     
_________________________________________________________________
batch_normalization_11 (Batc (None, 83)                332       
_________________________________________________________________
dropout_11 (Dropout)         (None, 83)                0         
_________________________________________________________________
dense_31 (Dense)             (None, 34)                2856      
_________________________________________________________________
batch_normalization_12 (Batc (None, 34)                136       
_________________________________________________________________
dropout_12 (Dropout)         (None, 34)                0         
_________________________________________________________________
dense_32 (Dense)             (None, 10)                350       
=================================================================
Total params: 686,533
Trainable params: 684,197
Non-trainable params: 2,336
_________________________________________________________________
```

In [0]:
```
# Compiling the model
model_2_drop.compile(optimizer='adam', loss='categorical_crossentropy', metric
s=['accuracy'])

# Fitting the model

history = model_2_drop.fit(X_train, Y_train, batch_size = batch_size, epochs =
nb_epoch, verbose=1, validation_data = (X_test, Y_test))
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 17s 276us/step - loss: 1.3228
- acc: 0.5787 - val_loss: 0.2892 - val_acc: 0.9192
Epoch 2/20
60000/60000 [==============================] - 14s 237us/step - loss: 0.5058
- acc: 0.8595 - val_loss: 0.1904 - val_acc: 0.9490
Epoch 3/20
60000/60000 [==============================] - 14s 237us/step - loss: 0.3545
- acc: 0.9100 - val_loss: 0.1504 - val_acc: 0.9596
Epoch 4/20
60000/60000 [==============================] - 14s 235us/step - loss: 0.2935
- acc: 0.9292 - val_loss: 0.1263 - val_acc: 0.9661
Epoch 5/20
60000/60000 [==============================] - 14s 235us/step - loss: 0.2576
- acc: 0.9379 - val_loss: 0.1281 - val_acc: 0.9682
Epoch 6/20
60000/60000 [==============================] - 14s 234us/step - loss: 0.2308
- acc: 0.9458 - val_loss: 0.1127 - val_acc: 0.9721
Epoch 7/20
60000/60000 [==============================] - 14s 236us/step - loss: 0.2067
- acc: 0.9514 - val_loss: 0.1093 - val_acc: 0.9715
Epoch 8/20
60000/60000 [==============================] - 14s 236us/step - loss: 0.1912
- acc: 0.9553 - val_loss: 0.1021 - val_acc: 0.9747
Epoch 9/20
60000/60000 [==============================] - 14s 235us/step - loss: 0.1823
- acc: 0.9578 - val_loss: 0.0959 - val_acc: 0.9762
Epoch 10/20
60000/60000 [==============================] - 14s 237us/step - loss: 0.1711
- acc: 0.9598 - val_loss: 0.0918 - val_acc: 0.9762
Epoch 11/20
60000/60000 [==============================] - 14s 237us/step - loss: 0.1628
- acc: 0.9613 - val_loss: 0.0918 - val_acc: 0.9775
Epoch 12/20
60000/60000 [==============================] - 15s 242us/step - loss: 0.1514
- acc: 0.9648 - val_loss: 0.0931 - val_acc: 0.9775
Epoch 13/20
60000/60000 [==============================] - 15s 250us/step - loss: 0.1484
- acc: 0.9659 - val_loss: 0.0922 - val_acc: 0.9784
Epoch 14/20
60000/60000 [==============================] - 14s 235us/step - loss: 0.1397
- acc: 0.9673 - val_loss: 0.0853 - val_acc: 0.9799
Epoch 15/20
60000/60000 [==============================] - 14s 237us/step - loss: 0.1390
- acc: 0.9675 - val_loss: 0.0811 - val_acc: 0.9806
Epoch 16/20
60000/60000 [==============================] - 14s 240us/step - loss: 0.1280
- acc: 0.9700 - val_loss: 0.0786 - val_acc: 0.9809
Epoch 17/20
60000/60000 [==============================] - 14s 239us/step - loss: 0.1215
- acc: 0.9716 - val_loss: 0.0842 - val_acc: 0.9800
Epoch 18/20
60000/60000 [==============================] - 14s 236us/step - loss: 0.1196
- acc: 0.9721 - val_loss: 0.0788 - val_acc: 0.9821
Epoch 19/20
60000/60000 [==============================] - 14s 237us/step - loss: 0.1168
```

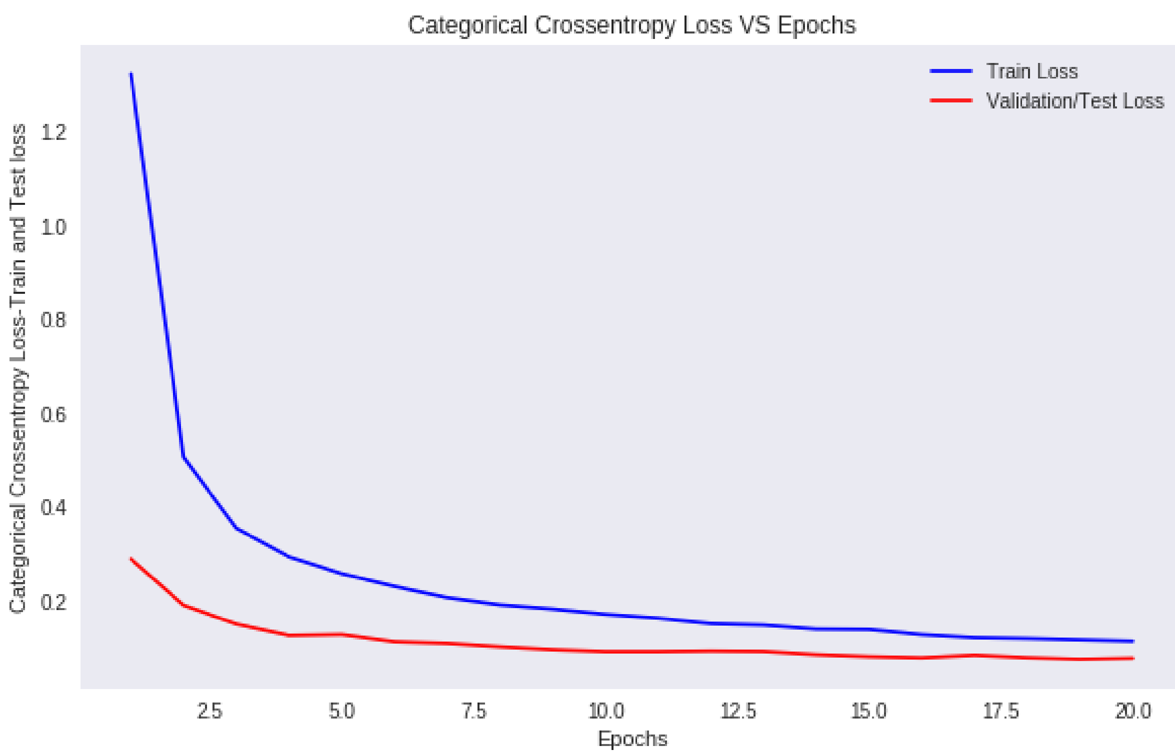
```
- acc: 0.9725 - val_loss: 0.0754 - val_acc: 0.9808
Epoch 20/20
60000/60000 [==============================] - 14s 235us/step - loss: 0.1139
- acc: 0.9728 - val_loss: 0.0776 - val_acc: 0.9815
```

5.5 Plotting the model values

In [0]:

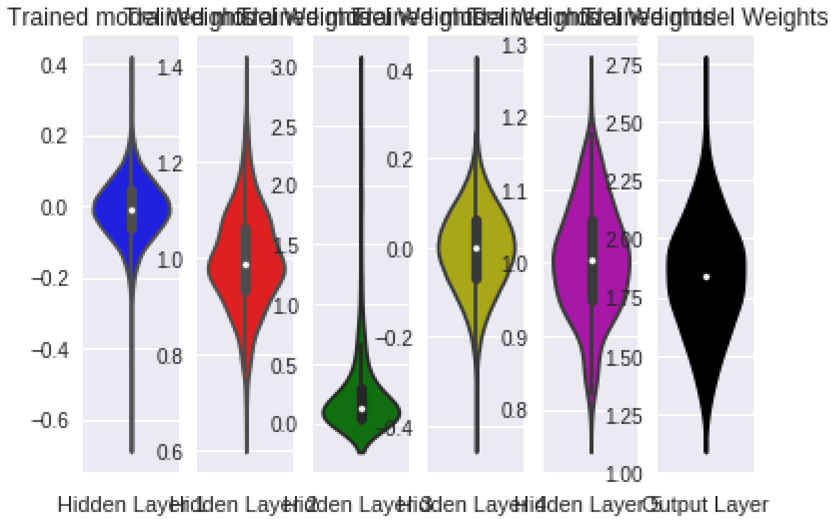
```
# Evaluating the model on test data
score_2_drop = model_2_drop.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score_2_drop[0])
print('Test accuracy:', score_2_drop[1])

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

# we will get val_loss and val_acc only when you pass the paramter validation_
data
# val_loss : validation loss
vy = history.history['val_loss']

# Training loss
ty = history.history['loss']
# calling the dynamic function to draw the plot
plt_dynamic(x, vy, ty)
```

```
Test score: 0.07762294698476326
Test accuracy: 0.9815
```



5.6 Plotting Violin plots of hidden and output layers to see weights distribution

In [0]:
```
w_after = model_2_drop.get_weights()

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

out_w = w_after[10].flatten().reshape(-1,1)


fig = plt.figure()
plt.title("Weight matrices after model trained\n")

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

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

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

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

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

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



6. Models Summarization

In [0]:
```
from pandas import DataFrame
MLP = {'MLP Layers':['2-hidden layer','2-hidden layer','3-hidden layer','3-hid
den layer','5-hidden layer','5-hidden layer'],
             'Model':['Model without dropout and Batch Normalization','Model w
ith dropout and Batch Normalization','Model without dropout and Batch Normaliz
ation',
             'Model with dropout and Batch Normalization','Model without dropo
ut and Batch Normalization','Model with dropout and Batch Normalization'],
             'Activation':['ReLU','ReLU','ReLU','ReLU','ReLU','ReLU'],'Optimiz
er':['Adam','Adam','Adam','Adam','Adam','Adam'],
             'Kernel_initializer':['he_normal','he_normal','he_normal','he_nor
mal','he_normal','he_normal'],
             'output layer':['softmax','softmax','softmax','softmax','softmax'
,'softmax'],
             'Training accuracy':['0.99','0.97','0.99','0.97','0.99','0.97'],
             'Train loss':['0.008','0.07','0.008','0.08','0.009','0.11'],
             'Test accuracy':['0.98','0.98','0.98','0.98','0.98','0.98'],
             'Test loss':['0.091','0.06','0.10','0.06','0.08','0.07']}
```

In [0]:
```
Final_conclusions = DataFrame(MLP)
Final_conclusions
```

Out[0]:

	Activation	Kernel_initializer	MLP Layers	Model	Optimizer	Test accuracy	Test loss	Train loss
0	ReLU	he_normal	2-hidden layer	Model without dropout and Batch Normalization	Adam	0.98	0.091	0.008
1	ReLU	he_normal	2-hidden layer	Model with dropout and Batch Normalization	Adam	0.98	0.06	0.07
2	ReLU	he_normal	3-hidden layer	Model without dropout and Batch Normalization	Adam	0.98	0.10	0.008
3	ReLU	he_normal	3-hidden layer	Model with dropout and Batch Normalization	Adam	0.98	0.06	0.08
4	ReLU	he_normal	5-hidden layer	Model without dropout and Batch Normalization	Adam	0.98	0.08	0.009
5	ReLU	he_normal	5-hidden layer	Model with dropout and Batch Normalization	Adam	0.98	0.07	0.11

7. Conclusions:-

From the above observations I can observed,

1. As I had used ReLU activation and Adam optimizer, all the accuracies are good.
2. Output layer is softmax layer
3. Models without dropout and normalization have less Test accuracy, and after adding dropout and normalization, model Test/validation accuracy improved, but there is no much difference in values.
4. With the add of dropout and normalization, the test loss also decreased.
5. In the Categorical Crossentropy Loss VS Epochs plot, train and test loss also converged or decreased gradually after adding dropout and normalization.
6. So by adding dropout and normalization, model worked well and gave good results.
7. I have used he_normal as kernel initializer as it have inbuilt mean and std values, without need of defing them explicitly.