Apply different Architectures on MNIST dataset using Keras

In [0]:

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

Load the data

In [0]:

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

In [0]:

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

In [125]:

```
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 [127]:

```
# 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 [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 [129]:

```
# 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 [130]:

```
# some model parameters
output_dim = 10
input_dim = X_train.shape[1]

batch_size = 112
nb_epoch = 20
print(input_dim)
```

```
784
```

Model 1 -> with 2 Hidden layers

1. MLP + ReLU + adam

In [131]:

```
# Multilayer perceptron

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

model_relu = Sequential()
model_relu.add(Dense(610, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNor
mal(mean=0.0, stddev=0.062, seed=None)))
model_relu.add(Dense(325, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.125
, seed=None)) )
model_relu.add(Dense(output_dim, activation='softmax'))

model_relu.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_72 (Dense)             (None, 610)               478850    
_________________________________________________________________
dense_73 (Dense)             (None, 325)               198575    
_________________________________________________________________
dense_74 (Dense)             (None, 10)                3260      
=================================================================
Total params: 680,685
Trainable params: 680,685
Non-trainable params: 0
_________________________________________________________________
```

In [132]:

```
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))
```

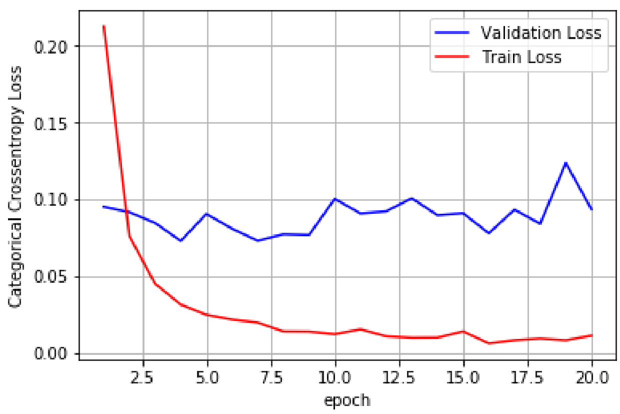
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 5s 76us/step - loss: 0.2126 - acc: 0.9360 - 
val_loss: 0.0952 - val_acc: 0.9696
Epoch 2/20
60000/60000 [==============================] - 3s 44us/step - loss: 0.0760 - acc: 0.9767 - 
val_loss: 0.0916 - val_acc: 0.9709
Epoch 3/20
60000/60000 [==============================] - 2s 40us/step - loss: 0.0451 - acc: 0.9859 - 
val_loss: 0.0846 - val_acc: 0.9722
Epoch 4/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.0315 - acc: 0.9900 - 
val_loss: 0.0729 - val_acc: 0.9783
Epoch 5/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.0248 - acc: 0.9919 - 
val_loss: 0.0905 - val_acc: 0.9730
Epoch 6/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.0217 - acc: 0.9925 - 
val_loss: 0.0808 - val_acc: 0.9774
Epoch 7/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.0197 - acc: 0.9932 - 
val_loss: 0.0730 - val_acc: 0.9797
Epoch 8/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.0139 - acc: 0.9953 - 
val_loss: 0.0772 - val_acc: 0.9803
Epoch 9/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.0138 - acc: 0.9954 - 
val_loss: 0.0768 - val_acc: 0.9814
Epoch 10/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.0122 - acc: 0.9960 - 
val_loss: 0.1004 - val_acc: 0.9773
Epoch 11/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.0153 - acc: 0.9947 - 
val_loss: 0.0908 - val_acc: 0.9803
Epoch 12/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.0108 - acc: 0.9962 - 
val_loss: 0.0922 - val_acc: 0.9790
Epoch 13/20
60000/60000 [==============================] - 2s 40us/step - loss: 0.0098 - acc: 0.9968 - 
val_loss: 0.1007 - val_acc: 0.9794
Epoch 14/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.0099 - acc: 0.9968 - 
val_loss: 0.0897 - val_acc: 0.9806
Epoch 15/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.0140 - acc: 0.9951 - 
val_loss: 0.0910 - val_acc: 0.9792
Epoch 16/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.0061 - acc: 0.9980 - 
val_loss: 0.0779 - val_acc: 0.9823
Epoch 17/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.0082 - acc: 0.9973 - 
val_loss: 0.0933 - val_acc: 0.9799
Epoch 18/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.0093 - acc: 0.9972 - 
```

```
val_loss: 0.0841 - val_acc: 0.9821
Epoch 19/20
60000/60000 [==============================] - 2s 40us/step - loss: 0.0082 - acc: 0.9975 -
val_loss: 0.1237 - val_acc: 0.9763
Epoch 20/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.0113 - acc: 0.9965 -
val_loss: 0.0936 - val_acc: 0.9800
```

In [133]:

```
#Evualate your model with accuracy and plot of (NUmber of epoches VS train_and_val_loss)

#Train accuracy
score = model_relu.evaluate(X_train, Y_train, verbose=0)
print('Train score:', score[0])
print('Train accuracy:', score[1]*100)

print('\n*********************** ********************\n')
#test accuracy
score = model_relu.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1]*100)


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

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

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

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

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

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

```
Train score: 0.009637041590256771
Train accuracy: 99.69833333333334

*********************** ********************

Test score: 0.09355196967310243
Test accuracy: 98.0
```



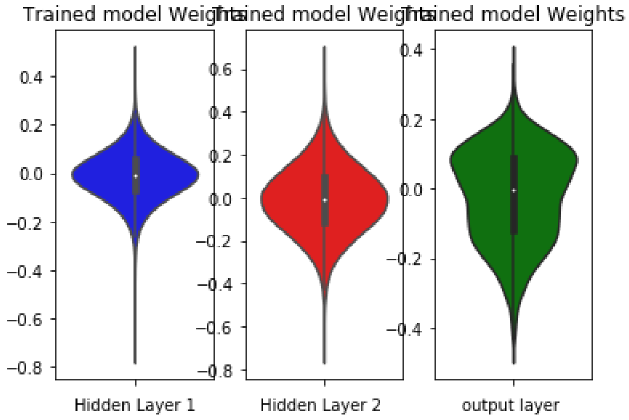
In [134]:

```
# Weights after trainning
#      1    2    3
```

```
#           1    2    3
# input->h1->h2->output
w_after = model_relu.get_weights()
# if 2 hidden layer then
# w_after[0]is the inpupt layer weights        w_after[1]is the input layer bias weights    input t
o hidden1
# w_after[2]is the hidde layer weights        w_after[3]is the hidde layer bias weights      hidde
to hidden2
# w_after[4]is the hidde layer weights        w_after[5]is the hidde layer bias weights      hidde
to output
h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
out_w = w_after[4].flatten().reshape(-1,1)

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

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


plt.subplot(1, 3, 3)
plt.title("Trained model Weights")
ax = sns.violinplot(y=out_w, color='g')
plt.xlabel('output layer ')
```

Out[134]:

```
Text(0.5, 0, 'output layer ')
```



2. MLP + ReLU + adam + batch__normalization

In [96]:

```
from keras.layers.normalization import BatchNormalization

model_batch = Sequential()

model_batch.add(Dense(610, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNo
rmal(mean=0.0, stddev=0.039, seed=None)))
model_batch.add(BatchNormalization())

model_batch.add(Dense(325, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.55
, seed=None)) )
model_batch.add(BatchNormalization())

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


model_batch.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_55 (Dense)             (None, 610)               478850    
_________________________________________________________________
batch_normalization_5 (Batch (None, 610)               2440      
_________________________________________________________________
dense_56 (Dense)             (None, 325)               198575    
_________________________________________________________________
batch_normalization_6 (Batch (None, 325)               1300      
_________________________________________________________________
dense_57 (Dense)             (None, 10)                3260      
=================================================================
Total params: 684,425
Trainable params: 682,555
Non-trainable params: 1,870
_________________________________________________________________
```

In [97]:

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

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

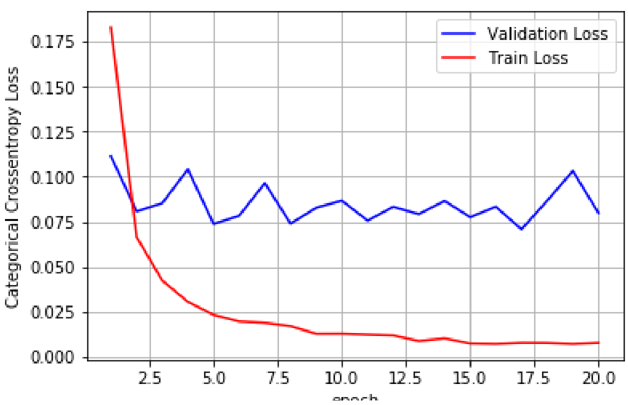
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 4s 74us/step - loss: 0.1828 - acc: 0.9454 - 
val_loss: 0.1113 - val_acc: 0.9660
Epoch 2/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.0665 - acc: 0.9795 - 
val_loss: 0.0807 - val_acc: 0.9743
Epoch 3/20
60000/60000 [==============================] - 3s 49us/step - loss: 0.0423 - acc: 0.9878 - 
val_loss: 0.0852 - val_acc: 0.9724
Epoch 4/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.0305 - acc: 0.9906 - 
val_loss: 0.1041 - val_acc: 0.9669
Epoch 5/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.0232 - acc: 0.9931 - 
val_loss: 0.0737 - val_acc: 0.9783
Epoch 6/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.0196 - acc: 0.9938 - 
val_loss: 0.0783 - val_acc: 0.9776
Epoch 7/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.0188 - acc: 0.9939 - 
val_loss: 0.0964 - val_acc: 0.9732
Epoch 8/20
60000/60000 [==============================] - 3s 53us/step - loss: 0.0170 - acc: 0.9943 - 
val_loss: 0.0739 - val_acc: 0.9799
Epoch 9/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.0127 - acc: 0.9961 - 
val_loss: 0.0827 - val_acc: 0.9768
Epoch 10/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.0128 - acc: 0.9957 - 
val_loss: 0.0867 - val_acc: 0.9758
Epoch 11/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.0123 - acc: 0.9960 - 
val_loss: 0.0756 - val_acc: 0.9790
Epoch 12/20
60000/60000 [==============================] - 3s 49us/step - loss: 0.0118 - acc: 0.9962 - 
val_loss: 0.0832 - val_acc: 0.9781
Epoch 13/20
60000/60000 [==============================] - 3s 49us/step - loss: 0.0087 - acc: 0.9971 - 
val_loss: 0.0792 - val_acc: 0.9805
Epoch 14/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.0102 - acc: 0.9967 - 
val_loss: 0.0865 - val_acc: 0.9785
Epoch 15/20
60000/60000 [==============================] - 3s 49us/step - loss: 0.0073 - acc: 0.9976 - 
val_loss: 0.0775 - val_acc: 0.9798
Epoch 16/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.0071 - acc: 0.9979 - 
val_loss: 0.0833 - val_acc: 0.9801
```

```
Epoch 17/20
60000/60000 [==============================] - 3s 49us/step - loss: 0.0077 - acc: 0.9974 -
val_loss: 0.0707 - val_acc: 0.9820
Epoch 18/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.0076 - acc: 0.9975 -
val_loss: 0.0866 - val_acc: 0.9796
Epoch 19/20
60000/60000 [==============================] - 3s 49us/step - loss: 0.0071 - acc: 0.9979 -
val_loss: 0.1031 - val_acc: 0.9772
Epoch 20/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.0077 - acc: 0.9975 -
val_loss: 0.0798 - val_acc: 0.9823
```

In [98]:

```python
#Evualate your model with accuracy and plot of (NUmber of epoches VS train_and_val_loss)

#Train accuracy
score = model_batch.evaluate(X_train, Y_train, verbose=0)
print('Train score:', score[0])
print('Train accuracy:', score[1]*100)

print('\n*********************** ********************\n')
#test accuracy
score = model_batch.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1]*100)


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

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

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

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

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

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

```
Train score: 0.0035421317501584024
Train accuracy: 99.88666666666667

*********************** ********************

Test score: 0.07983259213970796
Test accuracy: 98.22999999999999
```



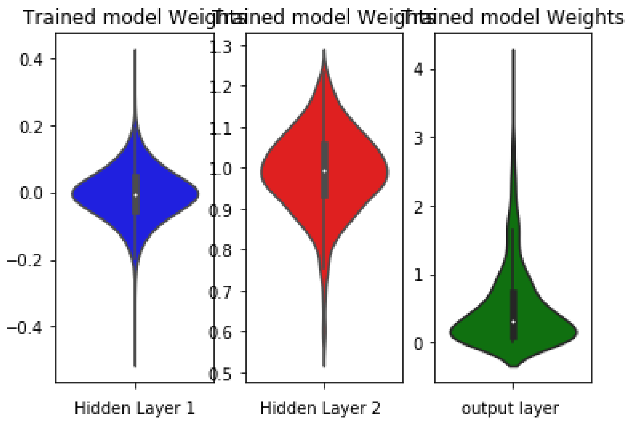
epoch

In [99]:

```
# Weights after trainning
#        1    2    3
# input->h1->h2->output
w_after = model_batch.get_weights()
# if 2 hidden layer then
# w_after[0]is the inpupt layer weights        w_after[1]is the input layer bias weights    input t
o hidden1
# w_after[2]is the hidde layer weights        w_after[3]is the hidde layer bias weights      hidde
to hidden2
# w_after[4]is the hidde layer weights        w_after[5]is the hidde layer bias weights      hidde
to output
h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
out_w = w_after[4].flatten().reshape(-1,1)

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

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


plt.subplot(1, 3, 3)
plt.title("Trained model Weights")
ax = sns.violinplot(y=out_w, color='g')
plt.xlabel('output layer ')
```

Out[99]:

```
Text(0.5, 0, 'output layer ')
```



3. MLP + ReLU + adam + dropout

In [100]:

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

from keras.layers import Dropout

model_drop = Sequential()

model_drop.add(Dense(610, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNor
mal(mean=0.0, stddev=0.039, seed=None)))
#model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))
```

```
model_drop.add(Dense(325, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.55, seed=None)) )
#model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

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


model_drop.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_58 (Dense)             (None, 610)               478850    
_________________________________________________________________
dropout_3 (Dropout)          (None, 610)               0         
_________________________________________________________________
dense_59 (Dense)             (None, 325)               198575    
_________________________________________________________________
dropout_4 (Dropout)          (None, 325)               0         
_________________________________________________________________
dense_60 (Dense)             (None, 10)                3260      
=================================================================
Total params: 680,685
Trainable params: 680,685
Non-trainable params: 0
_________________________________________________________________
```

In [103]:

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

history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=20, verbose=1, validation_data=(X_test, Y_test))
```

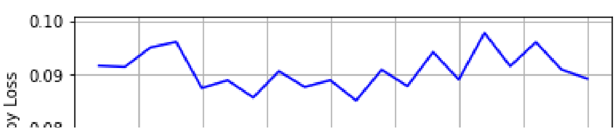
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 3s 58us/step - loss: 0.0490 - acc: 0.9868 - val_loss: 0.0916 - val_acc: 0.9831
Epoch 2/20
60000/60000 [==============================] - 2s 35us/step - loss: 0.0520 - acc: 0.9855 - val_loss: 0.0914 - val_acc: 0.9806
Epoch 3/20
60000/60000 [==============================] - 2s 35us/step - loss: 0.0505 - acc: 0.9858 - val_loss: 0.0950 - val_acc: 0.9795
Epoch 4/20
60000/60000 [==============================] - 2s 36us/step - loss: 0.0525 - acc: 0.9854 - val_loss: 0.0960 - val_acc: 0.9812
Epoch 5/20
60000/60000 [==============================] - 2s 35us/step - loss: 0.0503 - acc: 0.9861 - val_loss: 0.0875 - val_acc: 0.9820
Epoch 6/20
60000/60000 [==============================] - 2s 36us/step - loss: 0.0467 - acc: 0.9863 - val_loss: 0.0889 - val_acc: 0.9825
Epoch 7/20
60000/60000 [==============================] - 2s 35us/step - loss: 0.0485 - acc: 0.9865 - val_loss: 0.0857 - val_acc: 0.9820
Epoch 8/20
60000/60000 [==============================] - 2s 35us/step - loss: 0.0463 - acc: 0.9866 - val_loss: 0.0906 - val_acc: 0.9834
Epoch 9/20
60000/60000 [==============================] - 2s 36us/step - loss: 0.0454 - acc: 0.9878 - val_loss: 0.0877 - val_acc: 0.9810
Epoch 10/20
60000/60000 [==============================] - 2s 36us/step - loss: 0.0457 - acc: 0.9871 - val_loss: 0.0889 - val_acc: 0.9814
Epoch 11/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.0492 - acc: 0.9867 - val_loss: 0.0852 - val_acc: 0.9818
Epoch 12/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.0474 - acc: 0.9867 - val_loss: 0.0909 - val_acc: 0.9806
Epoch 13/20
60000/60000 [==============================] - 2s 40us/step - loss: 0.0434 - acc: 0.9873 -
```

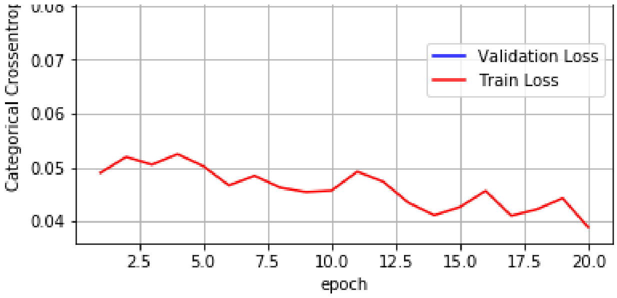
```
val_loss: 0.0878 - val_acc: 0.9828
Epoch 14/20
60000/60000 [==============================] - 2s 40us/step - loss: 0.0411 - acc: 0.9877 -
val_loss: 0.0942 - val_acc: 0.9810
Epoch 15/20
60000/60000 [==============================] - 2s 36us/step - loss: 0.0426 - acc: 0.9884 -
val_loss: 0.0891 - val_acc: 0.9831
Epoch 16/20
60000/60000 [==============================] - 2s 36us/step - loss: 0.0457 - acc: 0.9872 -
val_loss: 0.0977 - val_acc: 0.9813
Epoch 17/20
60000/60000 [==============================] - 2s 35us/step - loss: 0.0410 - acc: 0.9887 -
val_loss: 0.0915 - val_acc: 0.9802
Epoch 18/20
60000/60000 [==============================] - 2s 35us/step - loss: 0.0422 - acc: 0.9885 -
val_loss: 0.0960 - val_acc: 0.9817
Epoch 19/20
60000/60000 [==============================] - 2s 36us/step - loss: 0.0443 - acc: 0.9876 -
val_loss: 0.0909 - val_acc: 0.9818
Epoch 20/20
60000/60000 [==============================] - 2s 36us/step - loss: 0.0389 - acc: 0.9886 -
val_loss: 0.0892 - val_acc: 0.9831
```

In [105]:

```
#Evualate your model with accuracy and plot of (NUmber of epoches VS train_and_val_loss)

#Train accuracy
score = model_drop.evaluate(X_train, Y_train, verbose=0)
print('Train score:', score[0])
print('Train accuracy:', score[1]*100)

print('\n*********************** ********************\n')
#test accuracy
score = model_drop.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1]*100)


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

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

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

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

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

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

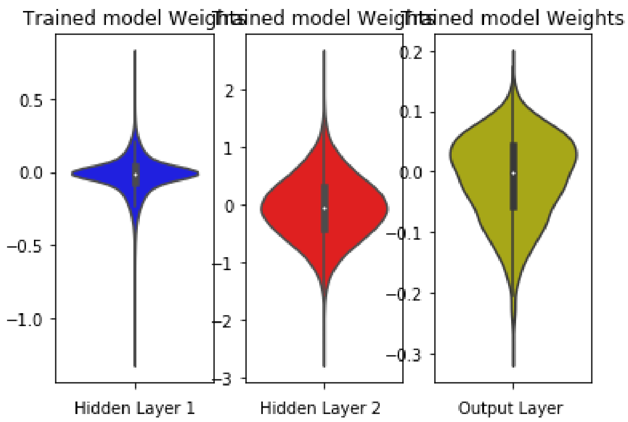
```
Train score: 0.004207986781747021
Train accuracy: 99.88333333333334

*********************** ********************

Test score: 0.08921634422981774
Test accuracy: 98.31
```





In [106]:

```
w_after = model_drop.get_weights()

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


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

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

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



4. MLP + ReLU + adam + dropout+ batch_normalization

In [107]:

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

from keras.layers import Dropout

model_drop = Sequential()

model_drop.add(Dense(610, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNormal(mean=0.0, stddev=0.039, seed=None)))
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

model_drop.add(Dense(325, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.55,
```

```
seed=None)) )
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

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


model_drop.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_61 (Dense)             (None, 610)               478850    
_________________________________________________________________
batch_normalization_7 (Batch (None, 610)               2440      
_________________________________________________________________
dropout_5 (Dropout)          (None, 610)               0         
_________________________________________________________________
dense_62 (Dense)             (None, 325)               198575    
_________________________________________________________________
batch_normalization_8 (Batch (None, 325)               1300      
_________________________________________________________________
dropout_6 (Dropout)          (None, 325)               0         
_________________________________________________________________
dense_63 (Dense)             (None, 10)                3260      
=================================================================
Total params: 684,425
Trainable params: 682,555
Non-trainable params: 1,870
_________________________________________________________________
```

In [108]:

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

history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=20, verbose=1, validation_
data=(X_test, Y_test))
```

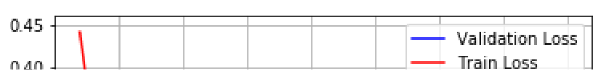
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 5s 85us/step - loss: 0.4413 - acc: 0.8667 -
val_loss: 0.1449 - val_acc: 0.9550
Epoch 2/20
60000/60000 [==============================] - 3s 54us/step - loss: 0.2196 - acc: 0.9331 -
val_loss: 0.1119 - val_acc: 0.9646
Epoch 3/20
60000/60000 [==============================] - 3s 54us/step - loss: 0.1736 - acc: 0.9466 -
val_loss: 0.1005 - val_acc: 0.9689
Epoch 4/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.1536 - acc: 0.9518 -
val_loss: 0.0898 - val_acc: 0.9716
Epoch 5/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.1305 - acc: 0.9603 -
val_loss: 0.0826 - val_acc: 0.9737
Epoch 6/20
60000/60000 [==============================] - 3s 54us/step - loss: 0.1228 - acc: 0.9612 -
val_loss: 0.0729 - val_acc: 0.9783
Epoch 7/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.1124 - acc: 0.9642 -
val_loss: 0.0731 - val_acc: 0.9778
Epoch 8/20
60000/60000 [==============================] - 3s 54us/step - loss: 0.1050 - acc: 0.9673 -
val_loss: 0.0669 - val_acc: 0.9803
Epoch 9/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.1005 - acc: 0.9694 -
val_loss: 0.0673 - val_acc: 0.9788
Epoch 10/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.0953 - acc: 0.9696 -
val_loss: 0.0666 - val_acc: 0.9807
Epoch 11/20
60000/60000 [==============================] - 4s 62us/step - loss: 0.0885 - acc: 0.9715 -
val_loss: 0.0682 - val_acc: 0.9798
Epoch 12/20
60000/60000 [==============================] - 4s 62us/step - loss: 0.0852 - acc: 0.9735 -
val_loss: 0.0673 - val_acc: 0.9806
```

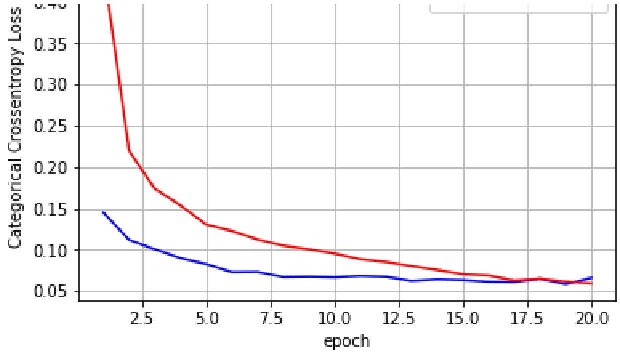
```
Epoch 13/20
60000/60000 [==============================] - 4s 60us/step - loss: 0.0802 - acc: 0.9741 -
val_loss: 0.0623 - val_acc: 0.9822
Epoch 14/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.0755 - acc: 0.9761 -
val_loss: 0.0642 - val_acc: 0.9808
Epoch 15/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.0704 - acc: 0.9772 -
val_loss: 0.0633 - val_acc: 0.9803
Epoch 16/20
60000/60000 [==============================] - 3s 54us/step - loss: 0.0688 - acc: 0.9780 -
val_loss: 0.0611 - val_acc: 0.9823
Epoch 17/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.0628 - acc: 0.9794 -
val_loss: 0.0607 - val_acc: 0.9823
Epoch 18/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.0648 - acc: 0.9787 -
val_loss: 0.0648 - val_acc: 0.9827
Epoch 19/20
60000/60000 [==============================] - 3s 54us/step - loss: 0.0614 - acc: 0.9800 -
val_loss: 0.0581 - val_acc: 0.9831
Epoch 20/20
60000/60000 [==============================] - 3s 54us/step - loss: 0.0590 - acc: 0.9806 -
val_loss: 0.0659 - val_acc: 0.9806
```

In [109]:

```
#Evualate your model with accuracy and plot of (NUmber of epoches VS train_and_val_loss)

#Train accuracy
score = model_drop.evaluate(X_train, Y_train, verbose=0)
print('Train score:', score[0])
print('Train accuracy:', score[1]*100)

print('\n************************ *********************\n')
#test accuracy
score = model_drop.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1]*100)


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

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

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

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

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

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

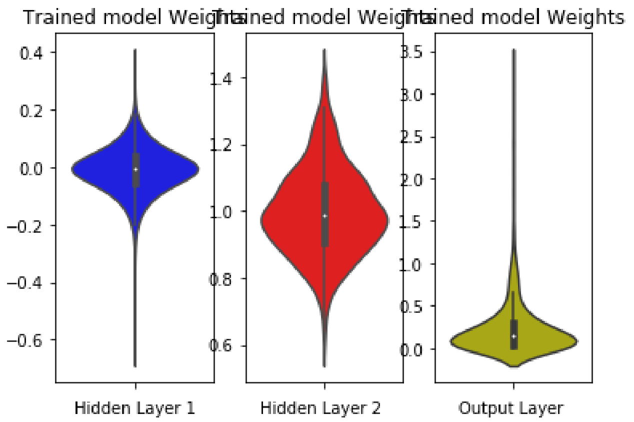
```
Train score: 0.017524294732744843
Train accuracy: 99.43666666666667

************************ *********************

Test score: 0.06593394307172858
Test accuracy: 98.06
```





In [110]:

```
w_after = model_drop.get_weights()

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


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

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

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



Model 2 -> with 3 Hidden layers

1. MLP + ReLU + adam

In [111]:

```
# Multilayer perceptron

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

```
# h2 =>  σ=√(2/(fan_in) = 0.125  => N(0,σ) = N(0,0.125)
# out =>  σ=√(2/(fan_in+1) = 0.120  => N(0,σ) = N(0,0.120)

model_relu = Sequential()
model_relu.add(Dense(610, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNor
mal(mean=0.0, stddev=0.062, seed=None)))
model_relu.add(Dense(420, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.125
, seed=None)) )
model_relu.add(Dense(210, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.125
, seed=None)) )
model_relu.add(Dense(output_dim, activation='softmax'))

model_relu.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_64 (Dense)             (None, 610)               478850    
_________________________________________________________________
dense_65 (Dense)             (None, 420)               256620    
_________________________________________________________________
dense_66 (Dense)             (None, 210)               88410     
_________________________________________________________________
dense_67 (Dense)             (None, 10)                2110      
=================================================================
Total params: 825,990
Trainable params: 825,990
Non-trainable params: 0
_________________________________________________________________
```

In [112]:

```
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))
```

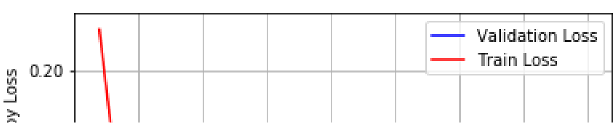
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 4s 67us/step - loss: 0.2283 - acc: 0.9317 -
val_loss: 0.1170 - val_acc: 0.9640
Epoch 2/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.0790 - acc: 0.9756 -
val_loss: 0.1085 - val_acc: 0.9655
Epoch 3/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.0545 - acc: 0.9825 -
val_loss: 0.0945 - val_acc: 0.9714
Epoch 4/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.0365 - acc: 0.9884 -
val_loss: 0.0739 - val_acc: 0.9794
Epoch 5/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.0321 - acc: 0.9899 -
val_loss: 0.0753 - val_acc: 0.9790
Epoch 6/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.0258 - acc: 0.9917 -
val_loss: 0.0899 - val_acc: 0.9762
Epoch 7/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.0228 - acc: 0.9924 -
val_loss: 0.1040 - val_acc: 0.9746
Epoch 8/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.0248 - acc: 0.9918 -
val_loss: 0.0756 - val_acc: 0.9812
Epoch 9/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.0189 - acc: 0.9940 -
val_loss: 0.0905 - val_acc: 0.9774
Epoch 10/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.0201 - acc: 0.9935 -
val_loss: 0.0902 - val_acc: 0.9775
Epoch 11/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.0146 - acc: 0.9956 -
val_loss: 0.0982 - val_acc: 0.9774
Epoch 12/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.0133 - acc: 0.9960 -
val_loss: 0.1027 - val_acc: 0.9783
Epoch 13/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.0188 - acc: 0.9942 -
```

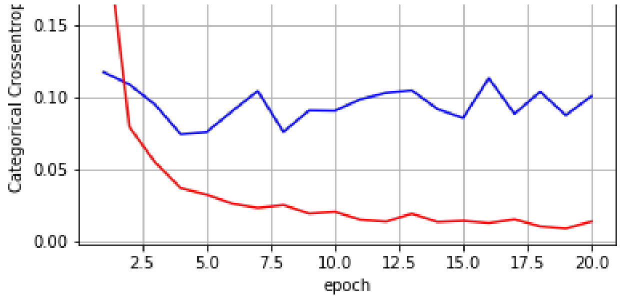
```
val_loss: 0.1044 - val_acc: 0.9764
Epoch 14/20
60000/60000 [==============================] - 2s 40us/step - loss: 0.0131 - acc: 0.9955 -
val_loss: 0.0914 - val_acc: 0.9799
Epoch 15/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.0139 - acc: 0.9958 -
val_loss: 0.0852 - val_acc: 0.9806
Epoch 16/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.0123 - acc: 0.9962 -
val_loss: 0.1129 - val_acc: 0.9780
Epoch 17/20
60000/60000 [==============================] - 2s 38us/step - loss: 0.0149 - acc: 0.9955 -
val_loss: 0.0881 - val_acc: 0.9811
Epoch 18/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.0100 - acc: 0.9971 -
val_loss: 0.1034 - val_acc: 0.9808
Epoch 19/20
60000/60000 [==============================] - 2s 40us/step - loss: 0.0085 - acc: 0.9973 -
val_loss: 0.0872 - val_acc: 0.9814
Epoch 20/20
60000/60000 [==============================] - 2s 39us/step - loss: 0.0134 - acc: 0.9958 -
val_loss: 0.1004 - val_acc: 0.9796
```

In [113]:

```python
#Evualate your model with accuracy and plot of (NUmber of epoches VS train_and_val_loss)

#Train accuracy
score = model_relu.evaluate(X_train, Y_train, verbose=0)
print('Train score:', score[0])
print('Train accuracy:', score[1]*100)

print('\n*********************** ********************\n')
#test accuracy
score = model_relu.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1]*100)


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

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

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

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

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

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

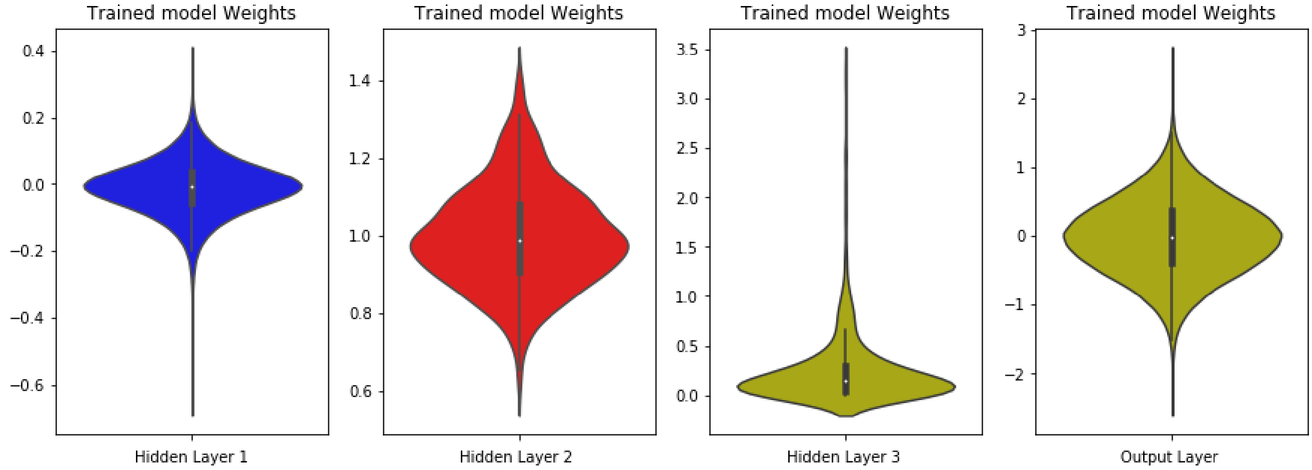
```
Train score: 0.007237614044734012
Train accuracy: 99.78666666666666

*********************** ********************

Test score: 0.10040943191677561
Test accuracy: 97.96000000000001
```





In [117]:

```
w_after = model_drop.get_weights()

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

fig = plt.figure(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='y')
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()
```



2. MLP + ReLU + adam +batch_normalization

In [135]:

```
from keras.layers.normalization import BatchNormalization

model_batch = Sequential()

model_batch.add(Dense(610, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNo
rmal(mean=0.0, stddev=0.039, seed=None)))
```

```
model_batch.add(BatchNormalization())

model_batch.add(Dense(420, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.55
, seed=None)) )
model_batch.add(BatchNormalization())

model_batch.add(Dense(210, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.55
, seed=None)) )
model_batch.add(BatchNormalization())


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


model_batch.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_75 (Dense)             (None, 610)               478850    
_________________________________________________________________
batch_normalization_12 (Batc (None, 610)               2440      
_________________________________________________________________
dense_76 (Dense)             (None, 420)               256620    
_________________________________________________________________
batch_normalization_13 (Batc (None, 420)               1680      
_________________________________________________________________
dense_77 (Dense)             (None, 210)               88410     
_________________________________________________________________
batch_normalization_14 (Batc (None, 210)               840       
_________________________________________________________________
dense_78 (Dense)             (None, 10)                2110      
=================================================================
Total params: 830,950
Trainable params: 828,470
Non-trainable params: 2,480
_________________________________________________________________
```

In [136]:

```
model_batch.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
history = model_batch.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, vali
dation_data=(X_test, Y_test))
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 7s 110us/step - loss: 0.1892 - acc: 0.9437 -
val_loss: 0.1007 - val_acc: 0.9676
Epoch 2/20
60000/60000 [==============================] - 4s 71us/step - loss: 0.0688 - acc: 0.9793 -
val_loss: 0.0889 - val_acc: 0.9710
Epoch 3/20
60000/60000 [==============================] - 4s 70us/step - loss: 0.0458 - acc: 0.9855 -
val_loss: 0.0869 - val_acc: 0.9726
Epoch 4/20
60000/60000 [==============================] - 4s 70us/step - loss: 0.0327 - acc: 0.9896 -
val_loss: 0.0758 - val_acc: 0.9770
Epoch 5/20
60000/60000 [==============================] - 4s 71us/step - loss: 0.0271 - acc: 0.9912 -
val_loss: 0.0836 - val_acc: 0.9747
Epoch 6/20
60000/60000 [==============================] - 4s 70us/step - loss: 0.0220 - acc: 0.9931 -
val_loss: 0.0776 - val_acc: 0.9786
Epoch 7/20
60000/60000 [==============================] - 4s 70us/step - loss: 0.0191 - acc: 0.9934 -
val_loss: 0.0807 - val_acc: 0.9790
Epoch 8/20
60000/60000 [==============================] - 4s 70us/step - loss: 0.0185 - acc: 0.9935 -
val_loss: 0.0759 - val_acc: 0.9779
Epoch 9/20
60000/60000 [==============================] - 4s 71us/step - loss: 0.0183 - acc: 0.9937 -
val_loss: 0.0761 - val_acc: 0.9794
Epoch 10/20
60000/60000 [==============================] - 4s 71us/step - loss: 0.0133 - acc: 0.9956 -
val_loss: 0.0782 - val_acc: 0.9787
```

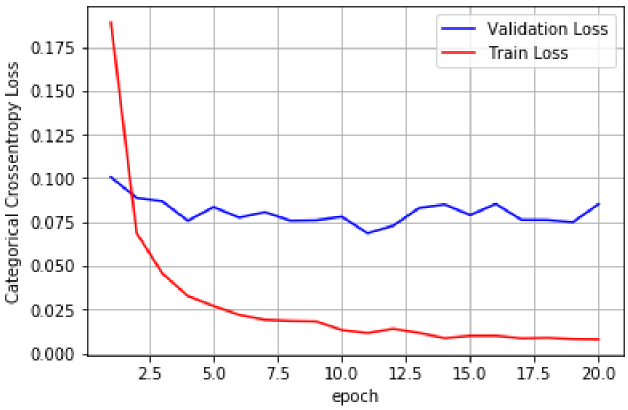
```
Epoch 11/20
60000/60000 [==============================] - 4s 70us/step - loss: 0.0116 - acc: 0.9961 -
val_loss: 0.0686 - val_acc: 0.9820
Epoch 12/20
60000/60000 [==============================] - 4s 70us/step - loss: 0.0140 - acc: 0.9953 -
val_loss: 0.0730 - val_acc: 0.9817
Epoch 13/20
60000/60000 [==============================] - 4s 70us/step - loss: 0.0117 - acc: 0.9962 -
val_loss: 0.0830 - val_acc: 0.9779
Epoch 14/20
60000/60000 [==============================] - 4s 71us/step - loss: 0.0086 - acc: 0.9970 -
val_loss: 0.0851 - val_acc: 0.9789
Epoch 15/20
60000/60000 [==============================] - 4s 70us/step - loss: 0.0100 - acc: 0.9965 -
val_loss: 0.0791 - val_acc: 0.9806
Epoch 16/20
60000/60000 [==============================] - 4s 71us/step - loss: 0.0100 - acc: 0.9965 -
val_loss: 0.0854 - val_acc: 0.9812
Epoch 17/20
60000/60000 [==============================] - 5s 80us/step - loss: 0.0086 - acc: 0.9970 -
val_loss: 0.0763 - val_acc: 0.9814
Epoch 18/20
60000/60000 [==============================] - 5s 81us/step - loss: 0.0089 - acc: 0.9971 -
val_loss: 0.0763 - val_acc: 0.9811
Epoch 19/20
60000/60000 [==============================] - 4s 72us/step - loss: 0.0082 - acc: 0.9973 -
val_loss: 0.0750 - val_acc: 0.9819
Epoch 20/20
60000/60000 [==============================] - 5s 76us/step - loss: 0.0079 - acc: 0.9974 -
val_loss: 0.0852 - val_acc: 0.9813
```

In [137]:

```
#Evualate your model with accuracy and plot of (NUmber of epoches VS train_and_val_loss)

#Train accuracy
score = model_batch.evaluate(X_train, Y_train, verbose=0)
print('Train score:', score[0])
print('Train accuracy:', score[1]*100)

print('\n*********************** ********************\n')
#test accuracy
score = model_batch.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1]*100)


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

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

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

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

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

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

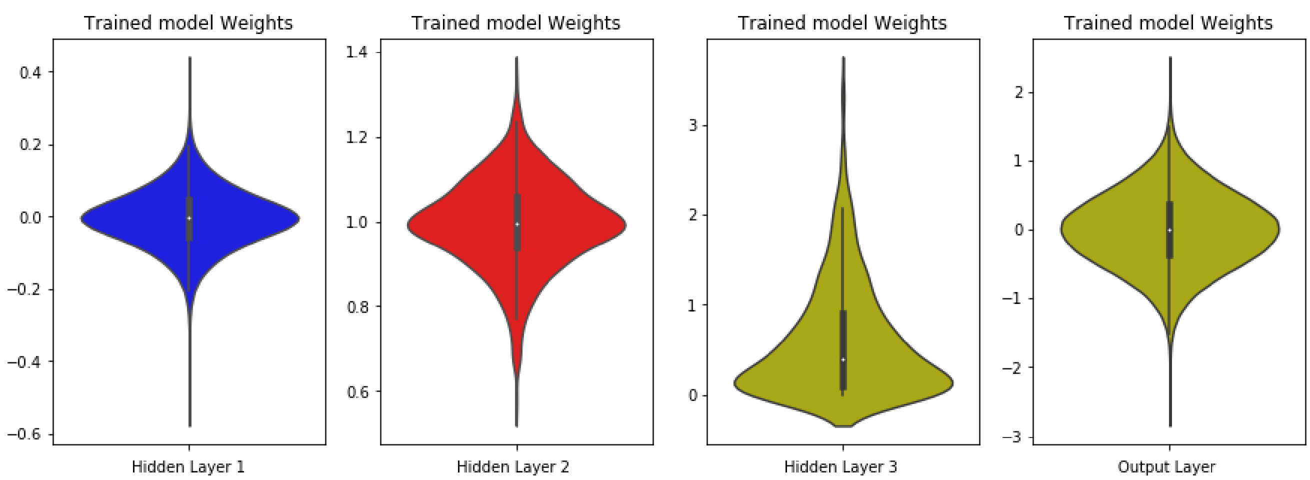
```
Train score: 0.0049123632065258185
Train accuracy: 99.86

*********************** ********************
```

```
Test score: 0.08521870328055128
Test accuracy: 98.13
```



In [138]:

```
w_after = model_batch.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='y')
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. MLP + ReLU + adam +dropout

In [139]:

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

from keras.layers import Dropout

model_drop = Sequential()

model_drop.add(Dense(610, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNormal(mean=0.0, stddev=0.039, seed=None)))
#model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

model_drop.add(Dense(420, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.55, seed=None)) )
#model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))


model_drop.add(Dense(210, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.55, seed=None)) )
#model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

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


model_drop.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_79 (Dense)             (None, 610)               478850    
_________________________________________________________________
dropout_7 (Dropout)          (None, 610)               0         
_________________________________________________________________
dense_80 (Dense)             (None, 420)               256620    
_________________________________________________________________
dropout_8 (Dropout)          (None, 420)               0         
_________________________________________________________________
dense_81 (Dense)             (None, 210)               88410     
_________________________________________________________________
dropout_9 (Dropout)          (None, 210)               0         
_________________________________________________________________
dense_82 (Dense)             (None, 10)                2110      
=================================================================
Total params: 825,990
Trainable params: 825,990
Non-trainable params: 0
_________________________________________________________________
```

In [140]:

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

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 5s 81us/step - loss: 11.1512 - acc: 0.2983 - val_loss: 7.3193 - val_acc: 0.5437
Epoch 2/20
60000/60000 [==============================] - 3s 44us/step - loss: 7.7638 - acc: 0.5111 - val_loss: 5.3495 - val_acc: 0.6641
Epoch 3/20
60000/60000 [==============================] - 3s 44us/step - loss: 6.2760 - acc: 0.6051 - val_loss: 4.4822 - val_acc: 0.7197
Epoch 4/20
60000/60000 [==============================] - 3s 44us/step - loss: 5.5289 - acc: 0.6528 - val_loss: 4.3106 - val_acc: 0.7305
Epoch 5/20
60000/60000 [==============================] - 3s 44us/step - loss: 5.2546 - acc: 0.6708 - val_loss: 4.2082 - val_acc: 0.7373
Epoch 6/20
```

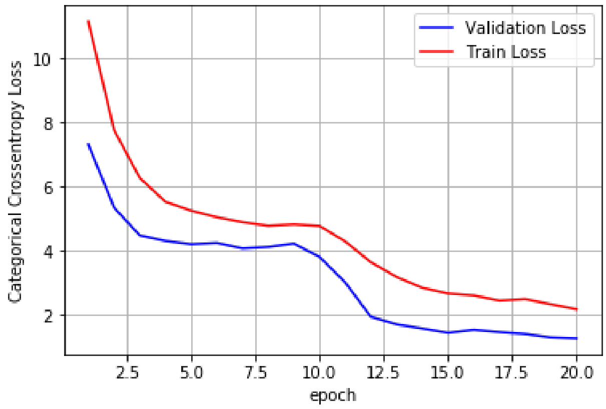
```
Epoch 6/20
60000/60000 [==============================] - 3s 44us/step - loss: 5.0519 - acc: 0.6835 -
val_loss: 4.2471 - val_acc: 0.7354
Epoch 7/20
60000/60000 [==============================] - 3s 44us/step - loss: 4.8966 - acc: 0.6935 -
val_loss: 4.0780 - val_acc: 0.7461
Epoch 8/20
60000/60000 [==============================] - 3s 44us/step - loss: 4.7825 - acc: 0.7013 -
val_loss: 4.1216 - val_acc: 0.7434
Epoch 9/20
60000/60000 [==============================] - 3s 44us/step - loss: 4.8263 - acc: 0.6986 -
val_loss: 4.2264 - val_acc: 0.7366
Epoch 10/20
60000/60000 [==============================] - 3s 50us/step - loss: 4.7764 - acc: 0.7012 -
val_loss: 3.8116 - val_acc: 0.7620
Epoch 11/20
60000/60000 [==============================] - 3s 50us/step - loss: 4.2936 - acc: 0.7303 -
val_loss: 3.0145 - val_acc: 0.8108
Epoch 12/20
60000/60000 [==============================] - 3s 51us/step - loss: 3.6466 - acc: 0.7706 -
val_loss: 1.9434 - val_acc: 0.8780
Epoch 13/20
60000/60000 [==============================] - 3s 47us/step - loss: 3.1846 - acc: 0.7993 -
val_loss: 1.7093 - val_acc: 0.8927
Epoch 14/20
60000/60000 [==============================] - 3s 45us/step - loss: 2.8491 - acc: 0.8208 -
val_loss: 1.5802 - val_acc: 0.8995
Epoch 15/20
60000/60000 [==============================] - 3s 44us/step - loss: 2.6713 - acc: 0.8320 -
val_loss: 1.4456 - val_acc: 0.9090
Epoch 16/20
60000/60000 [==============================] - 3s 44us/step - loss: 2.6102 - acc: 0.8361 -
val_loss: 1.5382 - val_acc: 0.9036
Epoch 17/20
60000/60000 [==============================] - 3s 44us/step - loss: 2.4493 - acc: 0.8463 -
val_loss: 1.4682 - val_acc: 0.9077
Epoch 18/20
60000/60000 [==============================] - 3s 44us/step - loss: 2.4974 - acc: 0.8431 -
val_loss: 1.4100 - val_acc: 0.9120
Epoch 19/20
60000/60000 [==============================] - 3s 44us/step - loss: 2.3377 - acc: 0.8533 -
val_loss: 1.3014 - val_acc: 0.9186
Epoch 20/20
60000/60000 [==============================] - 3s 44us/step - loss: 2.1831 - acc: 0.8630 -
val_loss: 1.2715 - val_acc: 0.9202
```

In [141]:

```python
#Evualate your model with accuracy and plot of (NUmber of epoches VS train_and_val_loss)

#Train accuracy
score = model_drop.evaluate(X_train, Y_train, verbose=0)
print('Train score:', score[0])
print('Train accuracy:', score[1]*100)

print('\n************************ *********************\n')
#test accuracy
score = model_drop.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1]*100)


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

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

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

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

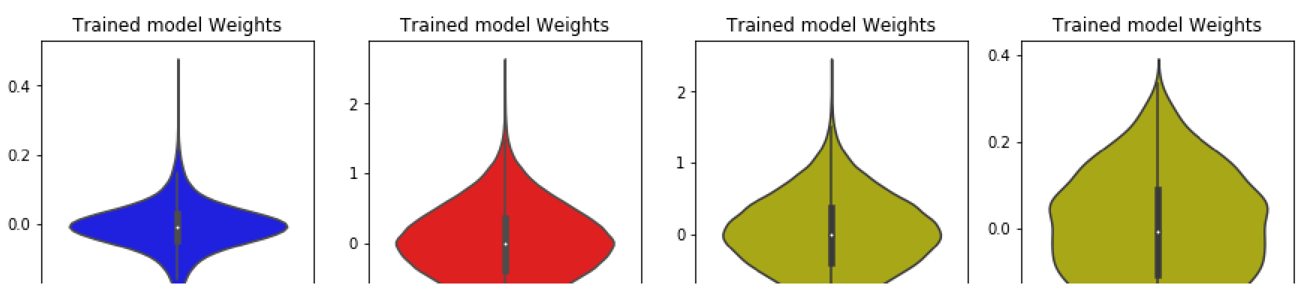
```
# loss : training loss
# acc : train accuracy
# for each key in histrory.histrory we will have a list of length equal to number of epochs

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

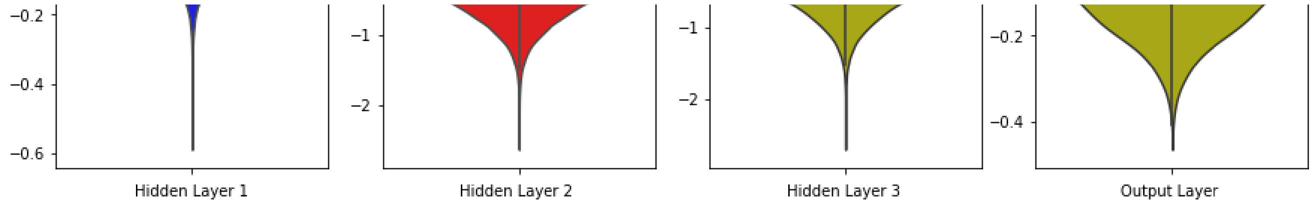
```
Train score: 1.2961381546263884
Train accuracy: 91.88166666666666

*********************** ********************

Test score: 1.2714586354423316
Test accuracy: 92.02
```



In [142]:

```
w_after = model_drop.get_weights()

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

fig = plt.figure(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='y')
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. MLP + ReLU + adam +dropout+batch_normalization

In [143]:

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

from keras.layers import Dropout

model_drop = Sequential()

model_drop.add(Dense(610, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNormal(mean=0.0, stddev=0.039, seed=None)))
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

model_drop.add(Dense(420, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.55, seed=None)) )
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))


model_drop.add(Dense(210, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.55, seed=None)) )
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

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


model_drop.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_83 (Dense)             (None, 610)               478850    
_________________________________________________________________
batch_normalization_15 (Batc (None, 610)               2440      
_________________________________________________________________
dropout_10 (Dropout)         (None, 610)               0         
_________________________________________________________________
dense_84 (Dense)             (None, 420)               256620    
_________________________________________________________________
batch_normalization_16 (Batc (None, 420)               1680      
_________________________________________________________________
dropout_11 (Dropout)         (None, 420)               0         
_________________________________________________________________
dense_85 (Dense)             (None, 210)               88410     
_________________________________________________________________
batch_normalization_17 (Batc (None, 210)               840       
_________________________________________________________________
dropout_12 (Dropout)         (None, 210)               0         
_________________________________________________________________
dense_86 (Dense)             (None, 10)                2110      
=================================================================
Total params: 830,950
Trainable params: 828,470
Non-trainable params: 2,480
_________________________________________________________________
```

In [144]:

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

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

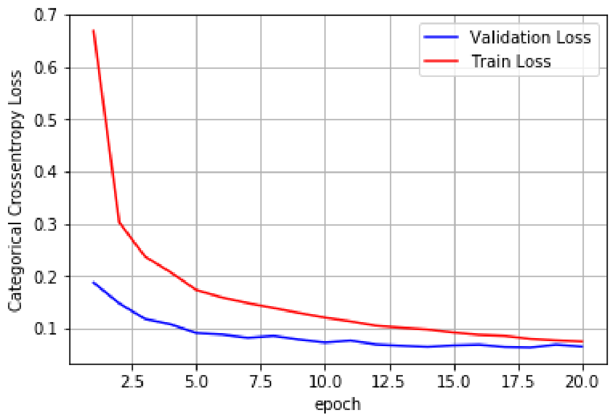
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 7s 121us/step - loss: 0.6685 - acc: 0.7927 -
val_loss: 0.1875 - val_acc: 0.9410
Epoch 2/20
60000/60000 [==============================] - 4s 74us/step - loss: 0.3027 - acc: 0.9084 -
val_loss: 0.1479 - val_acc: 0.9537
Epoch 3/20
60000/60000 [==============================] - 4s 74us/step - loss: 0.2374 - acc: 0.9285 -
val_loss: 0.1183 - val_acc: 0.9642
Epoch 4/20
60000/60000 [==============================] - 4s 73us/step - loss: 0.2073 - acc: 0.9391 -
val_loss: 0.1079 - val_acc: 0.9660
Epoch 5/20
60000/60000 [==============================] - 4s 74us/step - loss: 0.1733 - acc: 0.9479 -
val_loss: 0.0912 - val_acc: 0.9709
Epoch 6/20
60000/60000 [==============================] - 4s 74us/step - loss: 0.1592 - acc: 0.9524 -
val_loss: 0.0884 - val_acc: 0.9730
Epoch 7/20
60000/60000 [==============================] - 4s 74us/step - loss: 0.1485 - acc: 0.9557 -
val_loss: 0.0820 - val_acc: 0.9745
Epoch 8/20
60000/60000 [==============================] - 4s 73us/step - loss: 0.1392 - acc: 0.9583 -
val_loss: 0.0858 - val_acc: 0.9743
Epoch 9/20
60000/60000 [==============================] - 4s 74us/step - loss: 0.1297 - acc: 0.9607 -
val_loss: 0.0787 - val_acc: 0.9757
Epoch 10/20
60000/60000 [==============================] - 4s 74us/step - loss: 0.1207 - acc: 0.9635 -
val_loss: 0.0730 - val_acc: 0.9795
Epoch 11/20
60000/60000 [==============================] - 4s 73us/step - loss: 0.1135 - acc: 0.9649 -
val_loss: 0.0767 - val_acc: 0.9773
Epoch 12/20
60000/60000 [==============================] - 4s 75us/step - loss: 0.1052 - acc: 0.9678 -
val_loss: 0.0692 - val_acc: 0.9804
Epoch 13/20
60000/60000 [==============================] - 4s 74us/step - loss: 0.1014 - acc: 0.9687 -
val_loss: 0.0669 - val_acc: 0.9805
Epoch 14/20
60000/60000 [==============================] - 4s 73us/step - loss: 0.0980 - acc: 0.9702 -
val_loss: 0.0649 - val_acc: 0.9822
Epoch 15/20
60000/60000 [==============================] - 4s 74us/step - loss: 0.0923 - acc: 0.9725 -
val_loss: 0.0676 - val_acc: 0.9803
Epoch 16/20
60000/60000 [==============================] - 5s 83us/step - loss: 0.0877 - acc: 0.9725 -
val_loss: 0.0689 - val_acc: 0.9812
Epoch 17/20
60000/60000 [==============================] - 5s 85us/step - loss: 0.0857 - acc: 0.9737 -
val_loss: 0.0645 - val_acc: 0.9825
Epoch 18/20
60000/60000 [==============================] - 4s 75us/step - loss: 0.0800 - acc: 0.9757 -
val_loss: 0.0636 - val_acc: 0.9826
Epoch 19/20
60000/60000 [==============================] - 4s 75us/step - loss: 0.0770 - acc: 0.9759 -
val_loss: 0.0690 - val_acc: 0.9810
Epoch 20/20
60000/60000 [==============================] - 4s 74us/step - loss: 0.0749 - acc: 0.9766 -
val_loss: 0.0654 - val_acc: 0.9827
```

In [145]:

```
#Evualate your model with accuracy and plot of (NUmber of epoches VS train_and_val_loss)

#Train accuracy
score = model_drop.evaluate(X_train, Y_train, verbose=0)
print('Train score:', score[0])
print('Train accuracy:', score[1]*100)

print('\n*********************** ********************\n')
#test accuracy
```

```
#test accuracy
score = model_drop.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1]*100)


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

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

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

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

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

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

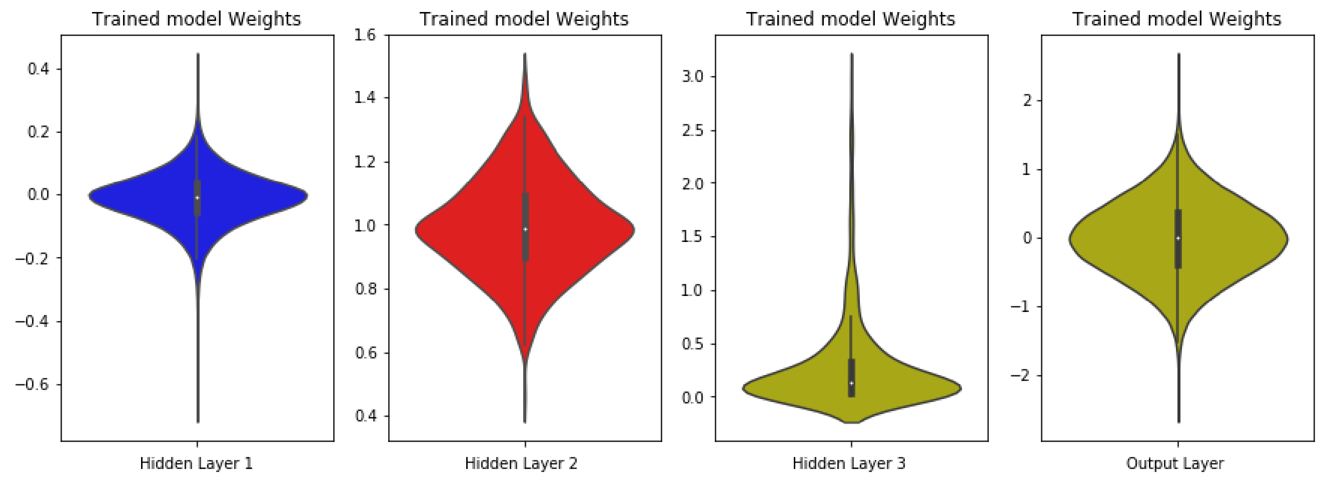
```
Train score: 0.019297944400046729
Train accuracy: 99.36500000000001

*********************** ********************

Test score: 0.06535992648077081
Test accuracy: 98.27
```



In [146]:

```
w_after = model_drop.get_weights()

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

fig = plt.figure(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")
```

```
plt.title("Trained model Weights")
ax = sns.violinplot(y=h3_w,color='y')
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()
```



Model 3 -> with 5 Hidden layers

1. MLP + ReLU + adam

In [156]:

```
# Multilayer perceptron

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

model_relu = Sequential()
model_relu.add(Dense(690, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNormal(mean=0.0, stddev=0.062, seed=None)))
model_relu.add(Dense(530, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.125, seed=None)) )
model_relu.add(Dense(412, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.125, seed=None)) )
model_relu.add(Dense(231, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.125, seed=None)) )
model_relu.add(Dense(112, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.125, seed=None)) )
model_relu.add(Dense(output_dim, activation='softmax'))

model_relu.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_99 (Dense)             (None, 690)               541650
_________________________________________________________________
dense_100 (Dense)            (None, 530)               366230
_________________________________________________________________
dense_101 (Dense)            (None, 412)               218772
_________________________________________________________________
dense_102 (Dense)            (None, 231)               95403
_________________________________________________________________
```

```
dense_103 (Dense)            (None, 112)              25984
_________________________________________________________________
dense_104 (Dense)            (None, 10)               1130
=================================================================
Total params: 1,249,169
Trainable params: 1,249,169
Non-trainable params: 0
_________________________________________________________________
```

In [157]:

```
model_relu.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
history = model_relu.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, valid
ation_data=(X_test, Y_test))
```

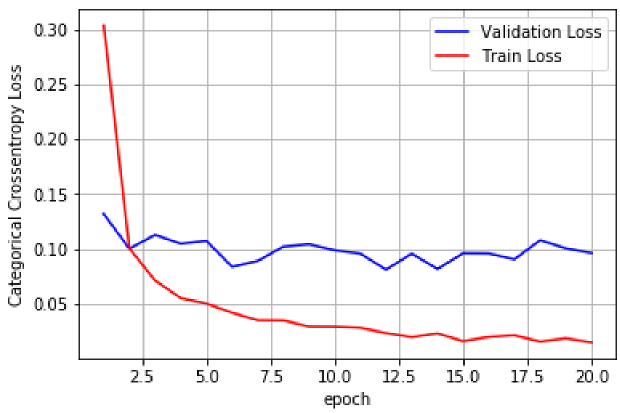
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 6s 100us/step - loss: 0.3034 - acc: 0.9205 -
val_loss: 0.1320 - val_acc: 0.9589
Epoch 2/20
60000/60000 [==============================] - 3s 54us/step - loss: 0.1008 - acc: 0.9691 -
val_loss: 0.1004 - val_acc: 0.9679
Epoch 3/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.0715 - acc: 0.9776 -
val_loss: 0.1130 - val_acc: 0.9669
Epoch 4/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.0555 - acc: 0.9824 -
val_loss: 0.1049 - val_acc: 0.9697
Epoch 5/20
60000/60000 [==============================] - 3s 49us/step - loss: 0.0505 - acc: 0.9839 -
val_loss: 0.1075 - val_acc: 0.9696
Epoch 6/20
60000/60000 [==============================] - 3s 48us/step - loss: 0.0422 - acc: 0.9864 -
val_loss: 0.0840 - val_acc: 0.9767
Epoch 7/20
60000/60000 [==============================] - 3s 49us/step - loss: 0.0354 - acc: 0.9887 -
val_loss: 0.0893 - val_acc: 0.9755
Epoch 8/20
60000/60000 [==============================] - 3s 49us/step - loss: 0.0352 - acc: 0.9890 -
val_loss: 0.1023 - val_acc: 0.9728
Epoch 9/20
60000/60000 [==============================] - 3s 49us/step - loss: 0.0296 - acc: 0.9909 -
val_loss: 0.1044 - val_acc: 0.9752
Epoch 10/20
60000/60000 [==============================] - 3s 49us/step - loss: 0.0295 - acc: 0.9909 -
val_loss: 0.0989 - val_acc: 0.9765
Epoch 11/20
60000/60000 [==============================] - 3s 49us/step - loss: 0.0285 - acc: 0.9911 -
val_loss: 0.0959 - val_acc: 0.9749
Epoch 12/20
60000/60000 [==============================] - 3s 48us/step - loss: 0.0237 - acc: 0.9927 -
val_loss: 0.0814 - val_acc: 0.9795
Epoch 13/20
60000/60000 [==============================] - 3s 49us/step - loss: 0.0200 - acc: 0.9938 -
val_loss: 0.0959 - val_acc: 0.9788
Epoch 14/20
60000/60000 [==============================] - 3s 48us/step - loss: 0.0234 - acc: 0.9932 -
val_loss: 0.0820 - val_acc: 0.9818
Epoch 15/20
60000/60000 [==============================] - 3s 48us/step - loss: 0.0164 - acc: 0.9952 -
val_loss: 0.0962 - val_acc: 0.9788
Epoch 16/20
60000/60000 [==============================] - 3s 49us/step - loss: 0.0202 - acc: 0.9941 -
val_loss: 0.0960 - val_acc: 0.9787
Epoch 17/20
60000/60000 [==============================] - 3s 49us/step - loss: 0.0216 - acc: 0.9935 -
val_loss: 0.0908 - val_acc: 0.9812
Epoch 18/20
60000/60000 [==============================] - 3s 49us/step - loss: 0.0160 - acc: 0.9951 -
val_loss: 0.1081 - val_acc: 0.9774
Epoch 19/20
60000/60000 [==============================] - 3s 48us/step - loss: 0.0189 - acc: 0.9948 -
val_loss: 0.1008 - val_acc: 0.9800
Epoch 20/20
60000/60000 [==============================] - 3s 48us/step - loss: 0.0152 - acc: 0.9956 -
val_loss: 0.0964 - val_acc: 0.9784
```

val_loss: 0.0964 - val_acc: 0.9784

In [158]:

```
#Evualate your model with accuracy and plot of (NUmber of epoches VS train_and_val_loss)

#Train accuracy
score = model_relu.evaluate(X_train, Y_train, verbose=0)
print('Train score:', score[0])
print('Train accuracy:', score[1]*100)

print('\n*********************** ********************\n')
#test accuracy
score = model_relu.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1]*100)


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

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

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

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

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

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

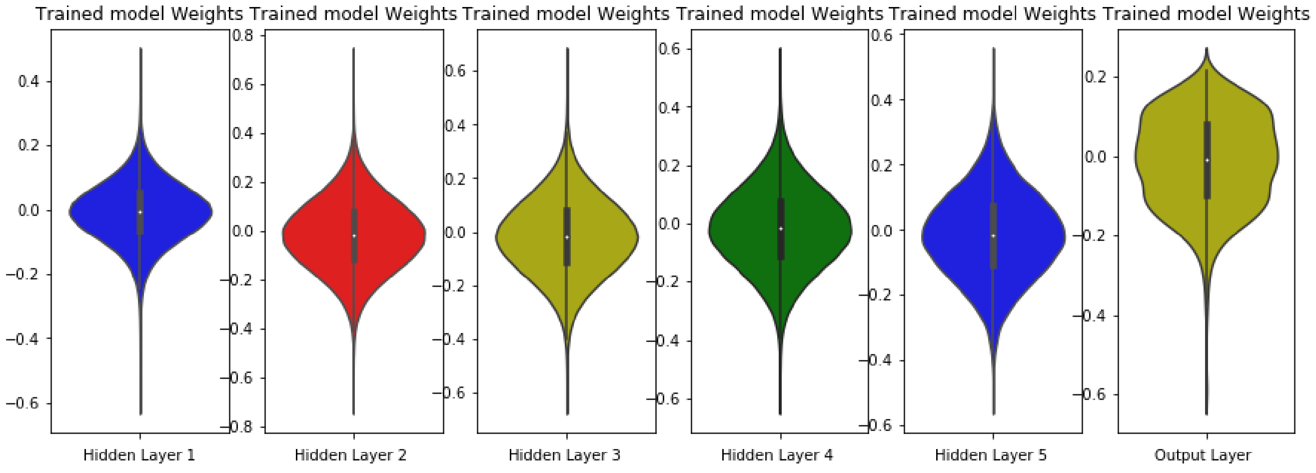
```
Train score: 0.013096415554758278
Train accuracy: 99.61

*********************** ********************

Test score: 0.09643159816987372
Test accuracy: 97.84
```



In [159]:

```
w_after = model_relu.get_weights()

h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
h3_w = w_after[4].flatten().reshape(-1,1)
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='y')
plt.xlabel('Hidden Layer 3 ')

plt.subplot(1, 6, 4)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h4_w,color='g')
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()
```



2. MLP + ReLU + adam +batch_normalization

In [160]:

```
# Multilayer perceptron

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

model_relu = Sequential()
model_relu.add(Dense(690, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNor
mal(mean=0.0, stddev=0.062, seed=None)))
model_relu.add(BatchNormalization())
model_relu.add(Dense(530, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.125
, seed=None)) )
```

```
model_relu.add(BatchNormalization())
model_relu.add(Dense(412, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.125
, seed=None)) )
model_relu.add(BatchNormalization())
model_relu.add(Dense(231, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.125
, seed=None)) )
model_relu.add(BatchNormalization())
model_relu.add(Dense(112, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.125
, seed=None)) )
model_relu.add(BatchNormalization())
model_relu.add(Dense(output_dim, activation='softmax'))

model_relu.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_105 (Dense)            (None, 690)               541650    
_________________________________________________________________
batch_normalization_23 (Batc (None, 690)               2760      
_________________________________________________________________
dense_106 (Dense)            (None, 530)               366230    
_________________________________________________________________
batch_normalization_24 (Batc (None, 530)               2120      
_________________________________________________________________
dense_107 (Dense)            (None, 412)               218772    
_________________________________________________________________
batch_normalization_25 (Batc (None, 412)               1648      
_________________________________________________________________
dense_108 (Dense)            (None, 231)               95403     
_________________________________________________________________
batch_normalization_26 (Batc (None, 231)               924       
_________________________________________________________________
dense_109 (Dense)            (None, 112)               25984     
_________________________________________________________________
batch_normalization_27 (Batc (None, 112)               448       
_________________________________________________________________
dense_110 (Dense)            (None, 10)                1130      
=================================================================
Total params: 1,257,069
Trainable params: 1,253,119
Non-trainable params: 3,950
_________________________________________________________________
```

In [161]:

```
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))
```

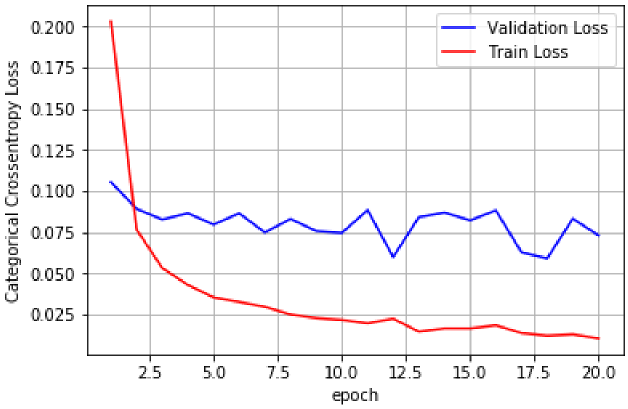
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 10s 172us/step - loss: 0.2029 - acc: 0.9385 - val_l
oss: 0.1053 - val_acc: 0.9673
Epoch 2/20
60000/60000 [==============================] - 6s 102us/step - loss: 0.0765 - acc: 0.9756 -
val_loss: 0.0890 - val_acc: 0.9730
Epoch 3/20
60000/60000 [==============================] - 6s 101us/step - loss: 0.0531 - acc: 0.9833 -
val_loss: 0.0825 - val_acc: 0.9743
Epoch 4/20
60000/60000 [==============================] - 6s 101us/step - loss: 0.0428 - acc: 0.9858 -
val_loss: 0.0864 - val_acc: 0.9762
Epoch 5/20
60000/60000 [==============================] - 6s 101us/step - loss: 0.0352 - acc: 0.9882 -
val_loss: 0.0795 - val_acc: 0.9765
Epoch 6/20
60000/60000 [==============================] - 6s 105us/step - loss: 0.0325 - acc: 0.9893 -
val_loss: 0.0863 - val_acc: 0.9753
Epoch 7/20
60000/60000 [==============================] - 7s 115us/step - loss: 0.0295 - acc: 0.9900 -
val_loss: 0.0747 - val_acc: 0.9785
Epoch 8/20
60000/60000 [==============================] - 6s 103us/step - loss: 0.0248 - acc: 0.9918 -
val_loss: 0.0829 - val_acc: 0.9771
```

```
val_loss: 0.0629 - val_acc: 0.9771
Epoch 9/20
60000/60000 [==============================] - 6s 100us/step - loss: 0.0226 - acc: 0.9925 -
val_loss: 0.0755 - val_acc: 0.9786
Epoch 10/20
60000/60000 [==============================] - 6s 100us/step - loss: 0.0215 - acc: 0.9927 -
val_loss: 0.0744 - val_acc: 0.9793
Epoch 11/20
60000/60000 [==============================] - 7s 113us/step - loss: 0.0195 - acc: 0.9936 -
val_loss: 0.0883 - val_acc: 0.9773
Epoch 12/20
60000/60000 [==============================] - 7s 113us/step - loss: 0.0223 - acc: 0.9926 -
val_loss: 0.0597 - val_acc: 0.9825
Epoch 13/20
60000/60000 [==============================] - 6s 101us/step - loss: 0.0144 - acc: 0.9952 -
val_loss: 0.0840 - val_acc: 0.9782
Epoch 14/20
60000/60000 [==============================] - 6s 101us/step - loss: 0.0163 - acc: 0.9944 -
val_loss: 0.0868 - val_acc: 0.9781
Epoch 15/20
60000/60000 [==============================] - 6s 101us/step - loss: 0.0163 - acc: 0.9945 -
val_loss: 0.0820 - val_acc: 0.9779
Epoch 16/20
60000/60000 [==============================] - 6s 100us/step - loss: 0.0183 - acc: 0.9938 -
val_loss: 0.0881 - val_acc: 0.9783
Epoch 17/20
60000/60000 [==============================] - 6s 106us/step - loss: 0.0135 - acc: 0.9956 -
val_loss: 0.0626 - val_acc: 0.9832
Epoch 18/20
60000/60000 [==============================] - 7s 109us/step - loss: 0.0119 - acc: 0.9961 -
val_loss: 0.0589 - val_acc: 0.9846
Epoch 19/20
60000/60000 [==============================] - 7s 109us/step - loss: 0.0127 - acc: 0.9957 -
val_loss: 0.0831 - val_acc: 0.9783
Epoch 20/20
60000/60000 [==============================] - 7s 113us/step - loss: 0.0103 - acc: 0.9965 -
val_loss: 0.0729 - val_acc: 0.9810
```

In [162]:

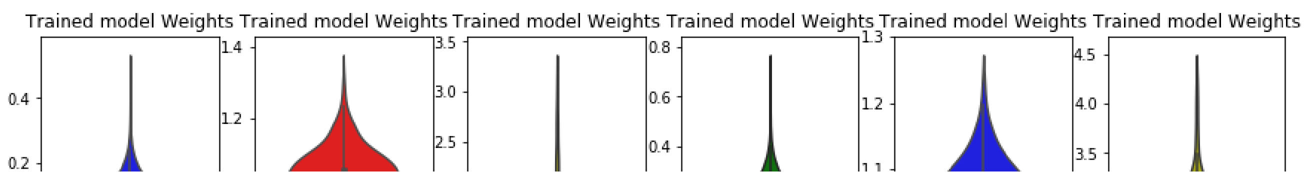
```
#Evualate your model with accuracy and plot of (NUmber of epoches VS train_and_val_loss)

#Train accuracy
score = model_relu.evaluate(X_train, Y_train, verbose=0)
print('Train score:', score[0])
print('Train accuracy:', score[1]*100)

print('\n*********************** ********************\n')
#test accuracy
score = model_relu.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1]*100)


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

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

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

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

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

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

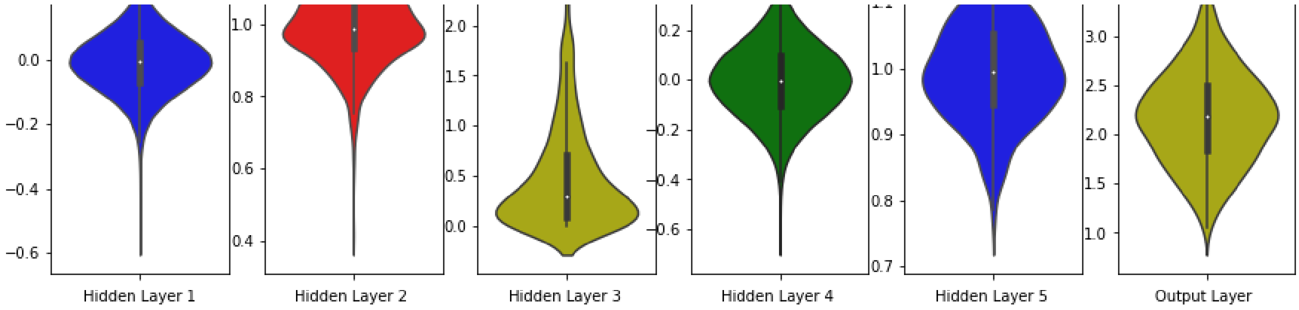
```
Train score: 0.005804570060232557
Train accuracy: 99.81166666666667

*********************** ********************

Test score: 0.07293605055603548
Test accuracy: 98.1
```



In [163]:

```
w_after = model_relu.get_weights()

h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
h3_w = w_after[4].flatten().reshape(-1,1)
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='y')
plt.xlabel('Hidden Layer 3 ')

plt.subplot(1, 6, 4)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h4_w,color='g')
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()
```





3. MLP + ReLU + adam + dropout

In [164]:

```
# Multilayer perceptron

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

model_relu = Sequential()
model_relu.add(Dense(690, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNor
mal(mean=0.0, stddev=0.062, seed=None)))
#model_relu.add(BatchNormalization())
model_relu.add(Dropout(0.5))

model_relu.add(Dense(530, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.125
, seed=None)) )
#model_relu.add(BatchNormalization())
model_relu.add(Dropout(0.5))

model_relu.add(Dense(412, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.125
, seed=None)) )
#model_relu.add(BatchNormalization())
model_relu.add(Dropout(0.5))

model_relu.add(Dense(231, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.125
, seed=None)) )
#model_relu.add(BatchNormalization())
model_relu.add(Dropout(0.5))

model_relu.add(Dense(112, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.125
, seed=None)) )
#model_relu.add(BatchNormalization())
model_relu.add(Dropout(0.5))

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

model_relu.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_111 (Dense)            (None, 690)               541650
_________________________________________________________________
dropout_13 (Dropout)         (None, 690)               0
_________________________________________________________________
dense_112 (Dense)            (None, 530)               366230
_________________________________________________________________
dropout_14 (Dropout)         (None, 530)               0
_________________________________________________________________
dense_113 (Dense)            (None, 412)               218772
_________________________________________________________________
dropout_15 (Dropout)         (None, 412)               0
_________________________________________________________________
dense_114 (Dense)            (None, 231)               95403
```

```
_________________________________________________________________
dropout_16 (Dropout)         (None, 231)              0
_________________________________________________________________
dense_115 (Dense)            (None, 112)              25984
_________________________________________________________________
dropout_17 (Dropout)         (None, 112)              0
_________________________________________________________________
dense_116 (Dense)            (None, 10)               1130
=================================================================
Total params: 1,249,169
Trainable params: 1,249,169
Non-trainable params: 0
_________________________________________________________________
```

In [165]:

```python
model_relu.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
history = model_relu.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, valid
ation_data=(X_test, Y_test))
```

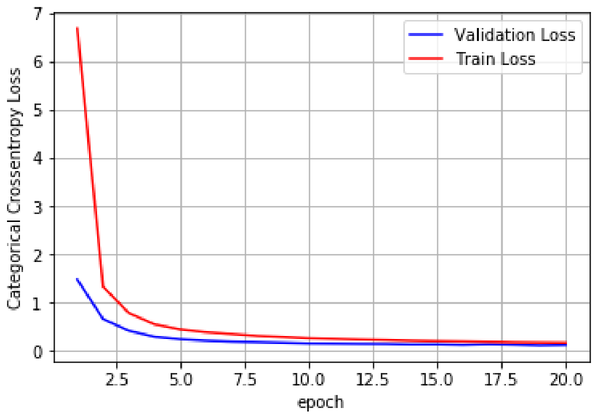
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 7s 113us/step - loss: 6.6817 - acc: 0.2389 -
val_loss: 1.4769 - val_acc: 0.5440
Epoch 2/20
60000/60000 [==============================] - 3s 54us/step - loss: 1.3284 - acc: 0.5313 -
val_loss: 0.6585 - val_acc: 0.8469
Epoch 3/20
60000/60000 [==============================] - 3s 54us/step - loss: 0.7840 - acc: 0.7597 -
val_loss: 0.4164 - val_acc: 0.8985
Epoch 4/20
60000/60000 [==============================] - 3s 54us/step - loss: 0.5498 - acc: 0.8459 -
val_loss: 0.2908 - val_acc: 0.9215
Epoch 5/20
60000/60000 [==============================] - 3s 54us/step - loss: 0.4436 - acc: 0.8826 -
val_loss: 0.2400 - val_acc: 0.9386
Epoch 6/20
60000/60000 [==============================] - 3s 54us/step - loss: 0.3852 - acc: 0.9027 -
val_loss: 0.2093 - val_acc: 0.9478
Epoch 7/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.3475 - acc: 0.9126 -
val_loss: 0.1893 - val_acc: 0.9519
Epoch 8/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.3082 - acc: 0.9242 -
val_loss: 0.1784 - val_acc: 0.9515
Epoch 9/20
60000/60000 [==============================] - 4s 62us/step - loss: 0.2862 - acc: 0.9276 -
val_loss: 0.1661 - val_acc: 0.9562
Epoch 10/20
60000/60000 [==============================] - 4s 62us/step - loss: 0.2601 - acc: 0.9369 -
val_loss: 0.1521 - val_acc: 0.9614
Epoch 11/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.2470 - acc: 0.9395 -
val_loss: 0.1485 - val_acc: 0.9630
Epoch 12/20
60000/60000 [==============================] - 3s 54us/step - loss: 0.2330 - acc: 0.9432 -
val_loss: 0.1439 - val_acc: 0.9642
Epoch 13/20
60000/60000 [==============================] - 4s 58us/step - loss: 0.2227 - acc: 0.9444 -
val_loss: 0.1411 - val_acc: 0.9638
Epoch 14/20
60000/60000 [==============================] - 4s 64us/step - loss: 0.2086 - acc: 0.9502 -
val_loss: 0.1313 - val_acc: 0.9673
Epoch 15/20
60000/60000 [==============================] - 4s 64us/step - loss: 0.1994 - acc: 0.9517 -
val_loss: 0.1325 - val_acc: 0.9682
Epoch 16/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.1931 - acc: 0.9531 -
val_loss: 0.1230 - val_acc: 0.9717
Epoch 17/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.1852 - acc: 0.9563 -
val_loss: 0.1351 - val_acc: 0.9674
Epoch 18/20
60000/60000 [==============================] - 3s 54us/step - loss: 0.1744 - acc: 0.9576 -
val_loss: 0.1252 - val_acc: 0.9712
Epoch 19/20
```

```
Epoch 19/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.1695 - acc: 0.9592 -
val_loss: 0.1118 - val_acc: 0.9731
Epoch 20/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.1660 - acc: 0.9605 -
val_loss: 0.1193 - val_acc: 0.9710
```

In [166]:

```
#Evualate your model with accuracy and plot of (NUmber of epoches VS train_and_val_loss)

#Train accuracy
score = model_relu.evaluate(X_train, Y_train, verbose=0)
print('Train score:', score[0])
print('Train accuracy:', score[1]*100)

print('\n*********************** ********************\n')
#test accuracy
score = model_relu.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1]*100)


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

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

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

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

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

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

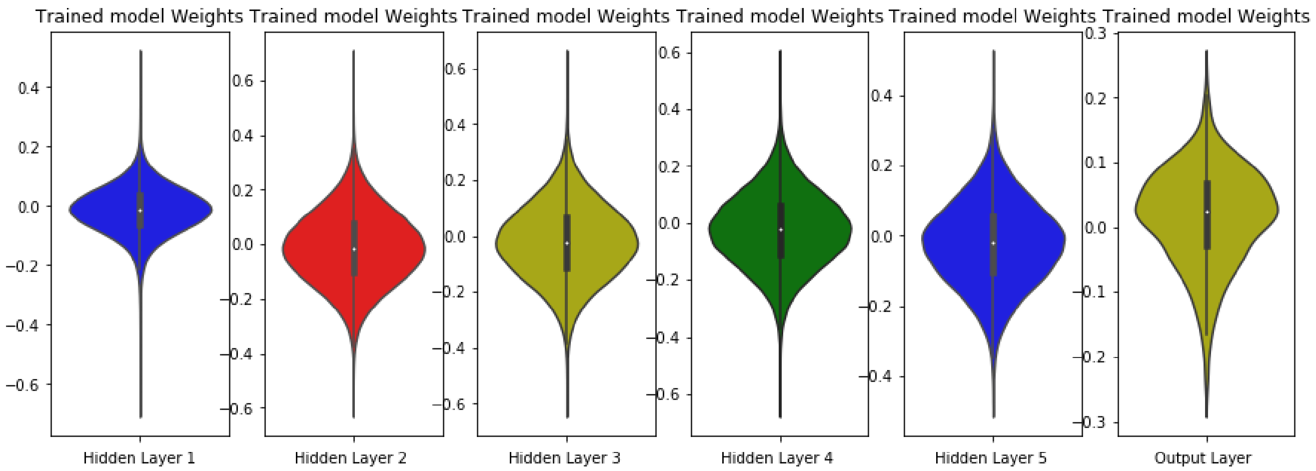
```
Train score: 0.06778361755032092
Train accuracy: 98.285

*********************** ********************

Test score: 0.11925422782022506
Test accuracy: 97.1
```



In [167]:

```
w_after = model_relu.get_weights()

h1_w = w_after[0].flatten().reshape(-1,1)
```

```
h2_w = w_after[2].flatten().reshape(-1,1)
h3_w = w_after[4].flatten().reshape(-1,1)
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='y')
plt.xlabel('Hidden Layer 3 ')

plt.subplot(1, 6, 4)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h4_w,color='g')
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()
```



4. MLP + ReLU + adam + dropout + batch_normalization

In [168]:

```
# Multilayer perceptron

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

model_relu = Sequential()
```

```
model_relu.add(Dense(690, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNor
mal(mean=0.0, stddev=0.062, seed=None)))
model_relu.add(BatchNormalization())
model_relu.add(Dropout(0.5))

model_relu.add(Dense(530, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.125
, seed=None)) )
model_relu.add(BatchNormalization())
model_relu.add(Dropout(0.5))

model_relu.add(Dense(412, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.125
, seed=None)) )
model_relu.add(BatchNormalization())
model_relu.add(Dropout(0.5))

model_relu.add(Dense(231, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.125
, seed=None)) )
model_relu.add(BatchNormalization())
model_relu.add(Dropout(0.5))

model_relu.add(Dense(112, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.125
, seed=None)) )
model_relu.add(BatchNormalization())
model_relu.add(Dropout(0.5))

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

model_relu.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_117 (Dense)            (None, 690)               541650    
_________________________________________________________________
batch_normalization_28 (Batc (None, 690)               2760      
_________________________________________________________________
dropout_18 (Dropout)         (None, 690)               0         
_________________________________________________________________
dense_118 (Dense)            (None, 530)               366230    
_________________________________________________________________
batch_normalization_29 (Batc (None, 530)               2120      
_________________________________________________________________
dropout_19 (Dropout)         (None, 530)               0         
_________________________________________________________________
dense_119 (Dense)            (None, 412)               218772    
_________________________________________________________________
batch_normalization_30 (Batc (None, 412)               1648      
_________________________________________________________________
dropout_20 (Dropout)         (None, 412)               0         
_________________________________________________________________
dense_120 (Dense)            (None, 231)               95403     
_________________________________________________________________
batch_normalization_31 (Batc (None, 231)               924       
_________________________________________________________________
dropout_21 (Dropout)         (None, 231)               0         
_________________________________________________________________
dense_121 (Dense)            (None, 112)               25984     
_________________________________________________________________
batch_normalization_32 (Batc (None, 112)               448       
_________________________________________________________________
dropout_22 (Dropout)         (None, 112)               0         
_________________________________________________________________
dense_122 (Dense)            (None, 10)                1130      
=================================================================
Total params: 1,257,069
Trainable params: 1,253,119
Non-trainable params: 3,950
_________________________________________________________________
```

In [169]:

```
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))
```

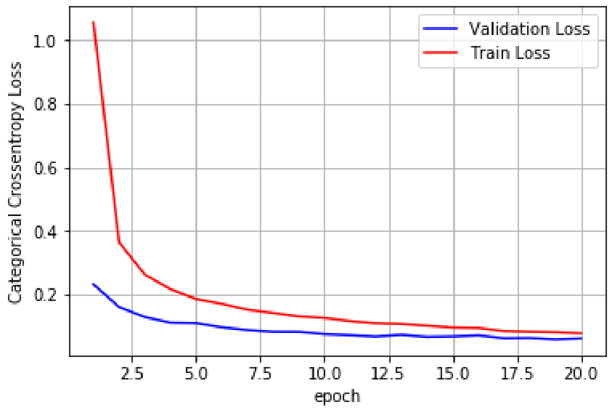
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 11s 182us/step - loss: 1.0551 - acc: 0.6702 - val_l
oss: 0.2329 - val_acc: 0.9293
Epoch 2/20
60000/60000 [==============================] - 6s 107us/step - loss: 0.3650 - acc: 0.8925 -
val_loss: 0.1617 - val_acc: 0.9511
Epoch 3/20
60000/60000 [==============================] - 6s 108us/step - loss: 0.2638 - acc: 0.9258 -
val_loss: 0.1304 - val_acc: 0.9640
Epoch 4/20
60000/60000 [==============================] - 6s 107us/step - loss: 0.2179 - acc: 0.9392 -
val_loss: 0.1127 - val_acc: 0.9680
Epoch 5/20
60000/60000 [==============================] - 6s 107us/step - loss: 0.1867 - acc: 0.9473 -
val_loss: 0.1113 - val_acc: 0.9688
Epoch 6/20
60000/60000 [==============================] - 6s 106us/step - loss: 0.1719 - acc: 0.9511 -
val_loss: 0.0982 - val_acc: 0.9723
Epoch 7/20
60000/60000 [==============================] - 6s 107us/step - loss: 0.1535 - acc: 0.9566 -
val_loss: 0.0894 - val_acc: 0.9743
Epoch 8/20
60000/60000 [==============================] - 6s 107us/step - loss: 0.1431 - acc: 0.9595 -
val_loss: 0.0841 - val_acc: 0.9770
Epoch 9/20
60000/60000 [==============================] - 7s 116us/step - loss: 0.1325 - acc: 0.9628 -
val_loss: 0.0838 - val_acc: 0.9769
Epoch 10/20
60000/60000 [==============================] - 7s 118us/step - loss: 0.1276 - acc: 0.9637 -
val_loss: 0.0768 - val_acc: 0.9803
Epoch 11/20
60000/60000 [==============================] - 6s 107us/step - loss: 0.1175 - acc: 0.9668 -
val_loss: 0.0734 - val_acc: 0.9804
Epoch 12/20
60000/60000 [==============================] - 6s 107us/step - loss: 0.1109 - acc: 0.9688 -
val_loss: 0.0691 - val_acc: 0.9808
Epoch 13/20
60000/60000 [==============================] - 7s 115us/step - loss: 0.1086 - acc: 0.9698 -
val_loss: 0.0746 - val_acc: 0.9799
Epoch 14/20
60000/60000 [==============================] - 7s 109us/step - loss: 0.1032 - acc: 0.9709 -
val_loss: 0.0680 - val_acc: 0.9811
Epoch 15/20
60000/60000 [==============================] - 7s 109us/step - loss: 0.0974 - acc: 0.9735 -
val_loss: 0.0693 - val_acc: 0.9809
Epoch 16/20
60000/60000 [==============================] - 6s 108us/step - loss: 0.0960 - acc: 0.9738 -
val_loss: 0.0728 - val_acc: 0.9804
Epoch 17/20
60000/60000 [==============================] - 6s 107us/step - loss: 0.0861 - acc: 0.9755 -
val_loss: 0.0635 - val_acc: 0.9829
Epoch 18/20
60000/60000 [==============================] - 6s 108us/step - loss: 0.0841 - acc: 0.9770 -
val_loss: 0.0645 - val_acc: 0.9821
Epoch 19/20
60000/60000 [==============================] - 6s 106us/step - loss: 0.0826 - acc: 0.9769 -
val_loss: 0.0601 - val_acc: 0.9843
Epoch 20/20
60000/60000 [==============================] - 6s 106us/step - loss: 0.0791 - acc: 0.9778 -
val_loss: 0.0630 - val_acc: 0.9837
```

In [170]:

```
#Evualate your model with accuracy and plot of (NUmber of epoches VS train_and_val_loss)

#Train accuracy
score = model_relu.evaluate(X_train, Y_train, verbose=0)
print('Train score:', score[0])
print('Train accuracy:', score[1]*100)

print('\n*********************** *********************\n')
#test accuracy
score = model_relu.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1]*100)
```

```
print('Test accuracy:', score[1]*100)


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

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

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

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

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

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

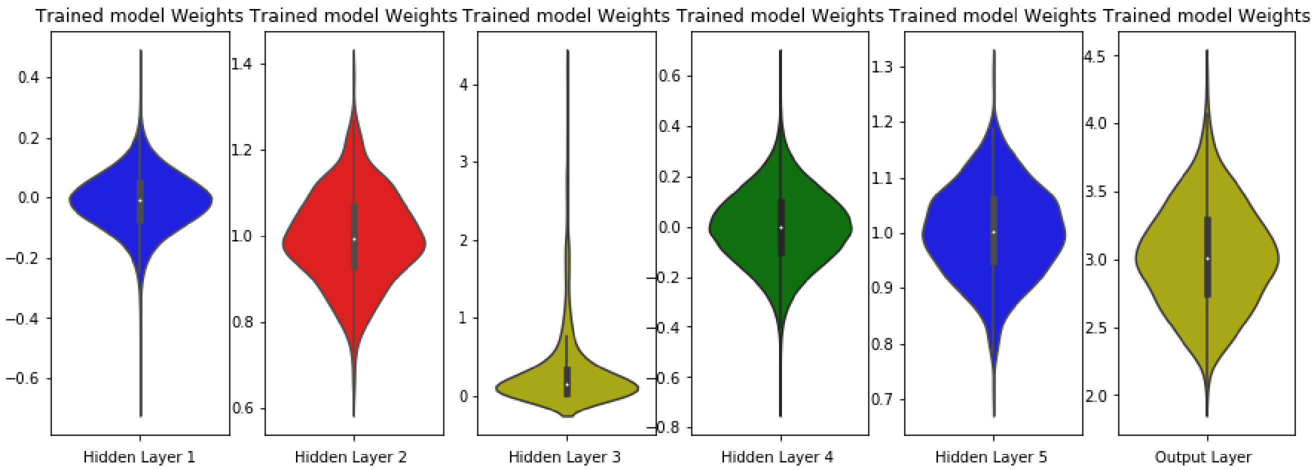
```
Train score: 0.020443898621193755
Train accuracy: 99.40833333333333

************************ ********************

Test score: 0.06300594019405543
Test accuracy: 98.37
```



In [171]:

```
w_after = model_relu.get_weights()

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

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

plt.subplot(1, 6, 4)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h4_w,color='g')
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()
```



COMPARE THE RESULTS IN PRETTY TABLE

In [183]:

```
from prettytable import PrettyTable
tb = PrettyTable()
tb.field_names= ("Hidden Layers", "Model", "Accuracy")
tb.add_row(["2", "MLP + ADAM + RELU",98.00])
tb.add_row(["2", "MLP + ADAM + RELU + batch_normalization",98.23])
tb.add_row(["2", "MLP + ADAM + RELU + dropout",98.31])
tb.add_row(["2", "MLP + ADAM + RELU + dropout+ batch_normalization",98.06])
tb.add_row([" ", " "," "])
tb.add_row([" ", " "," "])

tb.field_names= ("Hidden Layers", "Model", "Accuracy")
tb.add_row(["3", "MLP + ADAM + RELU",97.96])
tb.add_row(["3", "MLP + ADAM + RELU + batch_normalization",98.13])
tb.add_row(["3", "MLP + ADAM + RELU + dropout",92.02])
tb.add_row(["3", "MLP + ADAM + RELU + dropout+ batch_normalization",98.27])
tb.add_row([" ", " "," "])
tb.add_row([" ", " "," "])

tb.field_names= ("Hidden Layers", "Model", "Accuracy")
tb.add_row(["5", "MLP + ADAM + RELU",97.84])
tb.add_row(["5", "MLP + ADAM + RELU + batch_normalization",98.1])
tb.add_row(["5", "MLP + ADAM + RELU + dropout",97.1])
tb.add_row(["5", "MLP + ADAM + RELU + dropout+ batch_normalization",98.37])




print(tb.get_string(titles = "MLP Models - Observations"))
```

```
+---------------+---------------------------------------------------+----------+
```

Hidden Layers	Model	Accuracy
2	MLP + ADAM + RELU	98.0
2	MLP + ADAM + RELU + batch_normalization	98.23
2	MLP + ADAM + RELU + dropout	98.31
2	MLP + ADAM + RELU + dropout+ batch_normalization	98.06
3	MLP + ADAM + RELU	97.96
3	MLP + ADAM + RELU + batch_normalization	98.13
3	MLP + ADAM + RELU + dropout	92.02
3	MLP + ADAM + RELU + dropout+ batch_normalization	98.27
5	MLP + ADAM + RELU	97.84
5	MLP + ADAM + RELU + batch_normalization	98.1
5	MLP + ADAM + RELU + dropout	97.1
5	MLP + ADAM + RELU + dropout+ batch_normalization	98.37