In [1]:

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

```
Using TensorFlow backend.
```

In [2]:

```
#%matplotlib notebook
%matplotlib inline
%pylab 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()
```

```
Populating the interactive namespace from numpy and matplotlib
```

IMPORTING AND DIVING INTO THE DATASET

In [3]:

```
(X_train, y_train), (X_test, y_test) = mnist.load_data()
```

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

In [4]:

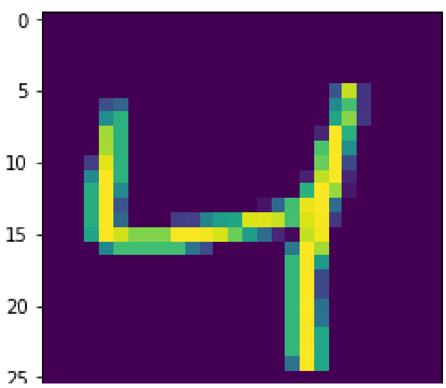
```
print("Number of training examples :", X_train.shape[0], "and each image is of shape (%d, %d)"%(X_train.shape[1], X_train.shape[2]))
print("Number of training examples :", X_test.shape[0], "and each image is of shape (%d, %d)"%(X_test.shape[1], X_test.shape[2]))
```

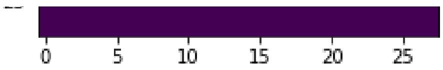
```
Number of training examples : 60000 and each image is of shape (28, 28)
Number of training examples : 10000 and each image is of shape (28, 28)
```

In [5]:

```
plt.imshow(X_train[2])
print("The output is",y_train[2])
```

```
The output is 4
```





In [0]:

```
X_train = X_train.reshape(X_train.shape[0], X_train.shape[1]*X_train.shape[2])
X_test = X_test.reshape(X_test.shape[0], X_test.shape[1]*X_test.shape[2])
```

In [7]:

```
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]:

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

In [9]:

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

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

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

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

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

In [0]:

```
from keras.models import Sequential
from keras.layers import Dense, Activation
```

In [0]:

```
output_dim = 10
input_dim = X_train.shape[1]

batch_size = 128
nb_epoch = 20
```

MODEL 1 - 2 HIDDEN LAYERS

1.1 RELU ACTIVATION

In [0]:

```
model1 = Sequential()
model1.add(Dense(230, input_dim=input_dim, activation='relu'))
model1.add(Dense(100, input_dim=input_dim, activation='relu'))
model1.add(Dense(10, input_dim=input_dim, activation='softmax'))
```

```
WARNING: Logging before flag parsing goes to stderr.
W0822 15:13:09.473532 140115941365632 deprecation_wrapper.py:119] From /usr/local/lib/pyt
hon3.6/dist-packages/keras/backend/tensorflow_backend.py:74: The name tf.get_default_grap
h is deprecated. Please use tf.compat.v1.get_default_graph instead.
```

```
W0822 15:13:09.522732 140115941365632 deprecation_wrapper.py:119] From /usr/local/lib/pyt
hon3.6/dist-packages/keras/backend/tensorflow_backend.py:517: The name tf.placeholder is
deprecated. Please use tf.compat.v1.placeholder instead.

W0822 15:13:09.530593 140115941365632 deprecation_wrapper.py:119] From /usr/local/lib/pyt
hon3.6/dist-packages/keras/backend/tensorflow_backend.py:4138: The name tf.random_uniform
is deprecated. Please use tf.random.uniform instead.
```

In [0]:

```
model1.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history = model1.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1
, validation_data=(X_test, Y_test))
```

```
W0822 15:13:14.105819 140115941365632 deprecation_wrapper.py:119] From /usr/local/lib/pyt
hon3.6/dist-packages/keras/optimizers.py:790: The name tf.train.Optimizer is deprecated.
Please use tf.compat.v1.train.Optimizer instead.

W0822 15:13:14.151415 140115941365632 deprecation_wrapper.py:119] From /usr/local/lib/pyt
hon3.6/dist-packages/keras/backend/tensorflow_backend.py:3295: The name tf.log is depreca
ted. Please use tf.math.log instead.

W0822 15:13:14.289976 140115941365632 deprecation.py:323] From /usr/local/lib/python3.6/d
ist-packages/tensorflow/python/ops/math_grad.py:1250: add_dispatch_support.<locals>.wrapp
er (from tensorflow.python.ops.array_ops) is deprecated and will be removed in a future v
ersion.
Instructions for updating:
Use tf.where in 2.0, which has the same broadcast rule as np.where
W0822 15:13:14.354537 140115941365632 deprecation_wrapper.py:119] From /usr/local/lib/pyt
hon3.6/dist-packages/keras/backend/tensorflow_backend.py:986: The name tf.assign_add is d
eprecated. Please use tf.compat.v1.assign_add instead.
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 7s 116us/step - loss: 0.2841 - acc: 0.9194
- val_loss: 0.1420 - val_acc: 0.9564
Epoch 2/20
60000/60000 [==============================] - 3s 48us/step - loss: 0.1106 - acc: 0.9673
- val_loss: 0.0923 - val_acc: 0.9710
Epoch 3/20
60000/60000 [==============================] - 3s 49us/step - loss: 0.0713 - acc: 0.9783
- val_loss: 0.0827 - val_acc: 0.9735
Epoch 4/20
60000/60000 [==============================] - 3s 49us/step - loss: 0.0525 - acc: 0.9837
- val_loss: 0.0799 - val_acc: 0.9741
Epoch 5/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.0382 - acc: 0.9885
- val_loss: 0.0801 - val_acc: 0.9764
Epoch 6/20
60000/60000 [==============================] - 3s 45us/step - loss: 0.0286 - acc: 0.9913
- val_loss: 0.0762 - val_acc: 0.9771
Epoch 7/20
60000/60000 [==============================] - 3s 45us/step - loss: 0.0231 - acc: 0.9926
- val_loss: 0.0733 - val_acc: 0.9780
Epoch 8/20
60000/60000 [==============================] - 3s 45us/step - loss: 0.0202 - acc: 0.9936
- val_loss: 0.0704 - val_acc: 0.9802
Epoch 9/20
60000/60000 [==============================] - 3s 47us/step - loss: 0.0160 - acc: 0.9949
- val_loss: 0.0788 - val_acc: 0.9785
Epoch 10/20
60000/60000 [==============================] - 3s 45us/step - loss: 0.0124 - acc: 0.9961
- val_loss: 0.0883 - val_acc: 0.9782
Epoch 11/20
60000/60000 [==============================] - 3s 47us/step - loss: 0.0141 - acc: 0.9952
- val_loss: 0.0886 - val_acc: 0.9782
Epoch 12/20
60000/60000 [==============================] - 3s 46us/step - loss: 0.0132 - acc: 0.9957
- val_loss: 0.0937 - val_acc: 0.9764
```

```
- val_loss: 0.0937 - val_acc: 0.9761
Epoch 13/20
60000/60000 [==============================] - 3s 47us/step - loss: 0.0089 - acc: 0.9971
- val_loss: 0.0780 - val_acc: 0.9815
Epoch 14/20
60000/60000 [==============================] - 3s 45us/step - loss: 0.0071 - acc: 0.9975
- val_loss: 0.0841 - val_acc: 0.9802
Epoch 15/20
60000/60000 [==============================] - 3s 46us/step - loss: 0.0137 - acc: 0.9955
- val_loss: 0.0879 - val_acc: 0.9793
Epoch 16/20
60000/60000 [==============================] - 3s 45us/step - loss: 0.0084 - acc: 0.9971
- val_loss: 0.0865 - val_acc: 0.9788
Epoch 17/20
60000/60000 [==============================] - 3s 46us/step - loss: 0.0058 - acc: 0.9982
- val_loss: 0.0994 - val_acc: 0.9786
Epoch 18/20
60000/60000 [==============================] - 3s 45us/step - loss: 0.0116 - acc: 0.9962
- val_loss: 0.0798 - val_acc: 0.9807
Epoch 19/20
60000/60000 [==============================] - 3s 45us/step - loss: 0.0072 - acc: 0.9975
- val_loss: 0.0874 - val_acc: 0.9802
Epoch 20/20
60000/60000 [==============================] - 3s 45us/step - loss: 0.0047 - acc: 0.9986
- val_loss: 0.0807 - val_acc: 0.9809
```

In [0]:

```
model1.summary()
```

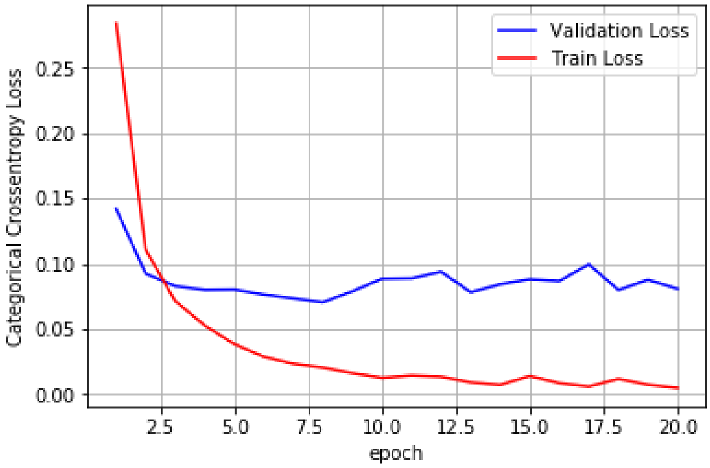
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_1 (Dense)              (None, 230)               180550    
_________________________________________________________________
dense_2 (Dense)              (None, 100)               23100     
_________________________________________________________________
dense_3 (Dense)              (None, 10)                1010      
=================================================================
Total params: 204,660
Trainable params: 204,660
Non-trainable params: 0
_________________________________________________________________
```

In [0]:

```
score = model1.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

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

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

# print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verb
ose=1, validation_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 epoc
hs

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

```
plt_dynamic(x, vy, ty, ax)
```

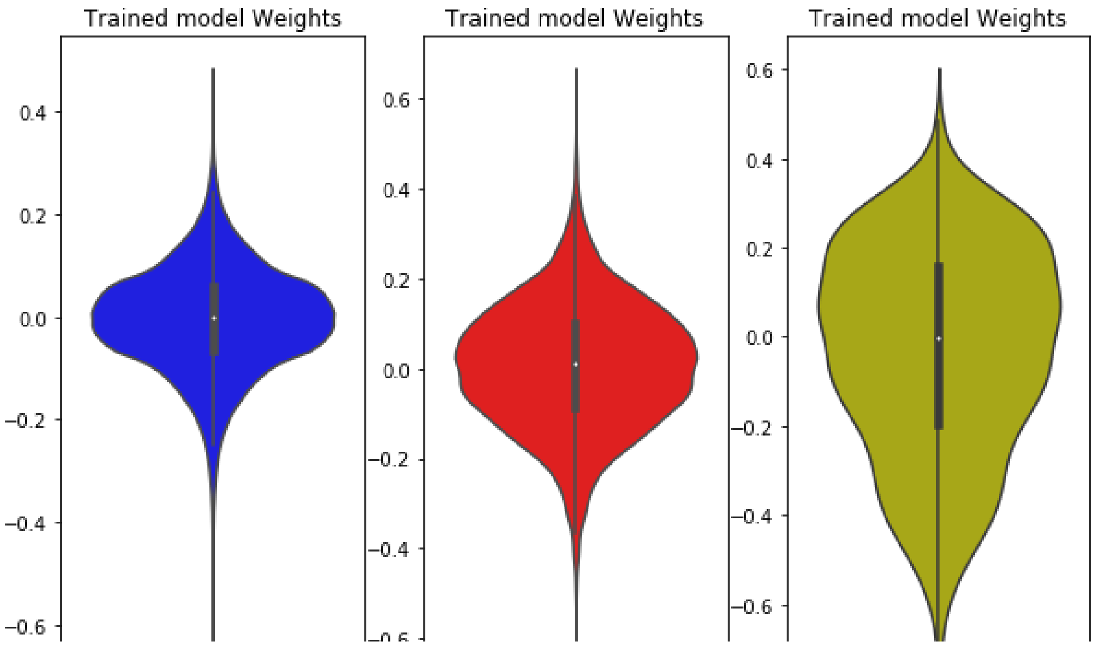
```
Test score: 0.08070132349427932
Test accuracy: 0.9809
```

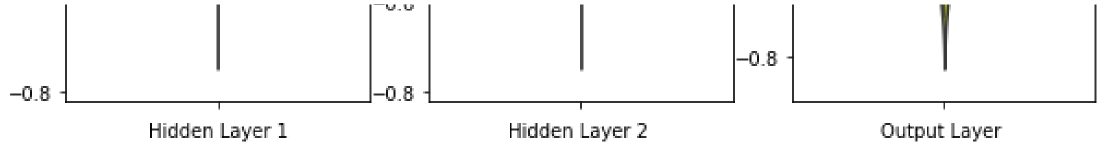


The plot says that Validation loss is very high than training loss after 3 epochs

In [0]:

```
w_after = model1.get_weights()

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


fig = plt.figure(figsize=(10,7))
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()
```





1.2 MODEL WITH 2 POWERS AS NUMBER OF HIDDEN LAYERS (RELU ACTIVATION)

In [0]:

```
model1 = Sequential()
model1.add(Dense(256, input_dim=input_dim, activation='relu'))
model1.add(Dense(128, input_dim=input_dim, activation='relu'))
model1.add(Dense(10, input_dim=input_dim, activation='softmax'))
```

In [0]:

```
model1.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history = model1.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 [==============================] - 3s 51us/step - loss: 0.2706 - acc: 0.9233
- val_loss: 0.1266 - val_acc: 0.9618
Epoch 2/20
60000/60000 [==============================] - 3s 45us/step - loss: 0.1033 - acc: 0.9690
- val_loss: 0.0958 - val_acc: 0.9689
Epoch 3/20
60000/60000 [==============================] - 3s 47us/step - loss: 0.0681 - acc: 0.9796
- val_loss: 0.0765 - val_acc: 0.9755
Epoch 4/20
60000/60000 [==============================] - 3s 45us/step - loss: 0.0479 - acc: 0.9853
- val_loss: 0.0738 - val_acc: 0.9760
Epoch 5/20
60000/60000 [==============================] - 3s 47us/step - loss: 0.0362 - acc: 0.9885
- val_loss: 0.0722 - val_acc: 0.9778
Epoch 6/20
60000/60000 [==============================] - 3s 45us/step - loss: 0.0280 - acc: 0.9912
- val_loss: 0.0737 - val_acc: 0.9783
Epoch 7/20
60000/60000 [==============================] - 3s 46us/step - loss: 0.0204 - acc: 0.9937
- val_loss: 0.0681 - val_acc: 0.9804
Epoch 8/20
60000/60000 [==============================] - 3s 44us/step - loss: 0.0195 - acc: 0.9934
- val_loss: 0.0733 - val_acc: 0.9795
Epoch 9/20
60000/60000 [==============================] - 3s 46us/step - loss: 0.0141 - acc: 0.9953
- val_loss: 0.0857 - val_acc: 0.9777
Epoch 10/20
60000/60000 [==============================] - 3s 45us/step - loss: 0.0148 - acc: 0.9953
- val_loss: 0.0783 - val_acc: 0.9786
Epoch 11/20
60000/60000 [==============================] - 3s 47us/step - loss: 0.0100 - acc: 0.9969
- val_loss: 0.1074 - val_acc: 0.9727
Epoch 12/20
60000/60000 [==============================] - 3s 47us/step - loss: 0.0123 - acc: 0.9957
- val_loss: 0.0991 - val_acc: 0.9750
Epoch 13/20
60000/60000 [==============================] - 3s 47us/step - loss: 0.0098 - acc: 0.9967
- val_loss: 0.0883 - val_acc: 0.9784
Epoch 14/20
60000/60000 [==============================] - 3s 47us/step - loss: 0.0077 - acc: 0.9975
- val_loss: 0.0950 - val_acc: 0.9782
Epoch 15/20
60000/60000 [==============================] - 3s 46us/step - loss: 0.0098 - acc: 0.9965
- val_loss: 0.1035 - val_acc: 0.9773
Epoch 16/20
60000/60000 [==============================] - 3s 46us/step - loss: 0.0059 - acc: 0.9980
- val_loss: 0.0860 - val_acc: 0.9803
```

```
Epoch 17/20
60000/60000 [==============================] - 3s 46us/step - loss: 0.0090 - acc: 0.9966
- val_loss: 0.0943 - val_acc: 0.9784
Epoch 18/20
60000/60000 [==============================] - 3s 46us/step - loss: 0.0092 - acc: 0.9970
- val_loss: 0.1059 - val_acc: 0.9787
Epoch 19/20
60000/60000 [==============================] - 3s 47us/step - loss: 0.0056 - acc: 0.9980
- val_loss: 0.1003 - val_acc: 0.9781
Epoch 20/20
60000/60000 [==============================] - 3s 46us/step - loss: 0.0067 - acc: 0.9978
- val_loss: 0.0951 - val_acc: 0.9802
```

In [0]:

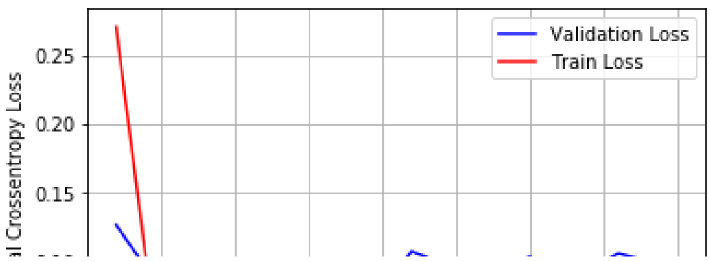
```
model1.summary()
```

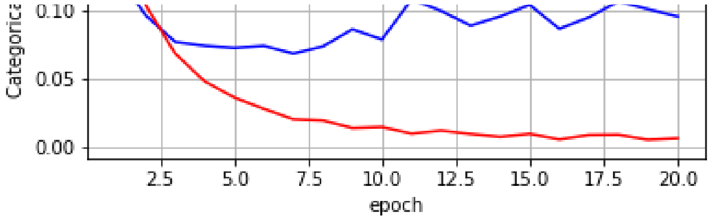
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_4 (Dense)              (None, 256)               200960    
_________________________________________________________________
dense_5 (Dense)              (None, 128)               32896     
_________________________________________________________________
dense_6 (Dense)              (None, 10)                1290      
=================================================================
Total params: 235,146
Trainable params: 235,146
Non-trainable params: 0
_________________________________________________________________
```

In [0]:

```
score = model1.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

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

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

# print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verb
ose=1, validation_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 epoc
hs

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

```
Test score: 0.09506374017388317
Test accuracy: 0.9802
```

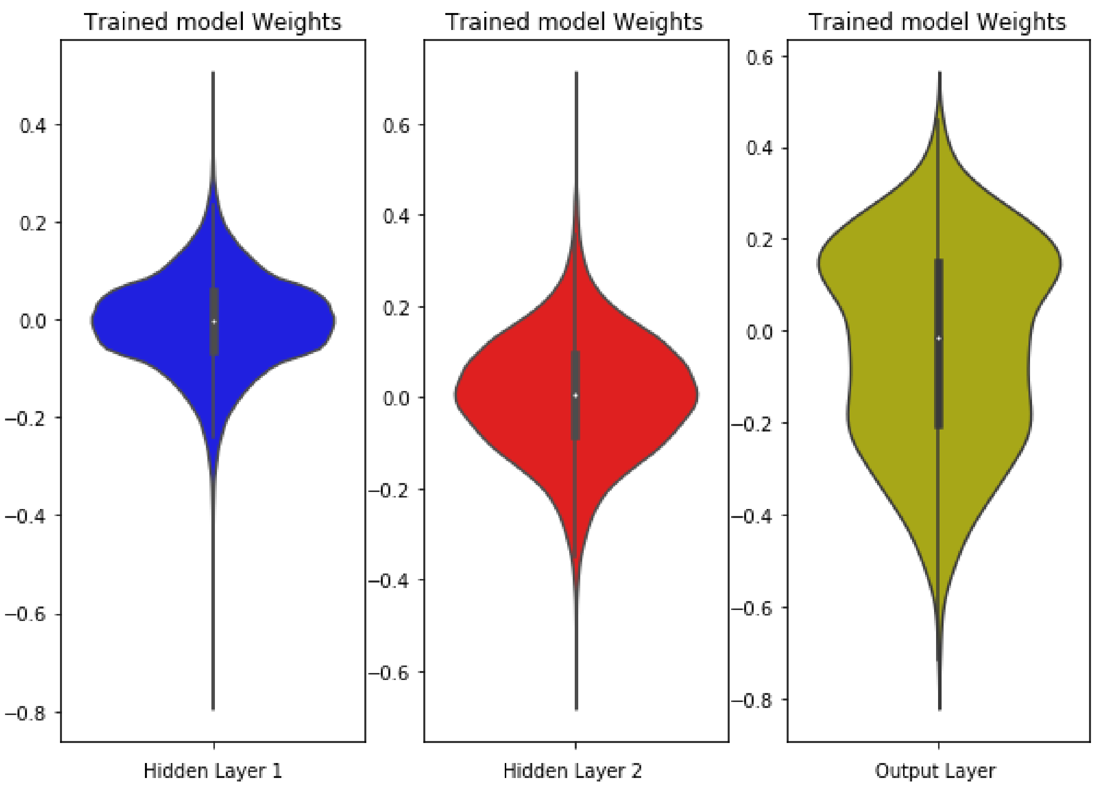




The model overfits as the number of epochs increased.

In [0]:

```
w_after = model1.get_weights()

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


fig = plt.figure(figsize=(10,7))
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()
```



1.3 RELU ACTIVATION WITH DROPOUT VALUE 0.5

In [0]:

```
from keras.layers import Dropout
model1 = Sequential()
```

```
model1.add(Dense(256, input_dim=input_dim, activation='relu'))
model1.add(Dropout(0.5))
model1.add(Dense(128, input_dim=input_dim, activation='relu'))
model1.add(Dropout(0.5))
model1.add(Dense(10, input_dim=input_dim, activation='softmax'))
```

```
W0822 15:32:48.802173 140115941365632 deprecation.py:506] From /usr/local/lib/python3.6/d
ist-packages/keras/backend/tensorflow_backend.py:3445: calling dropout (from tensorflow.p
ython.ops.nn_ops) with keep_prob is deprecated and will be removed in a future version.
Instructions for updating:
Please use `rate` instead of `keep_prob`. Rate should be set to `rate = 1 - keep_prob`.
```

In [0]:

```
model1.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history = model1.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 [==============================] - 3s 53us/step - loss: 0.5257 - acc: 0.8390
- val_loss: 0.1702 - val_acc: 0.9497
Epoch 2/20
60000/60000 [==============================] - 3s 49us/step - loss: 0.2422 - acc: 0.9304
- val_loss: 0.1223 - val_acc: 0.9646
Epoch 3/20
60000/60000 [==============================] - 3s 49us/step - loss: 0.1883 - acc: 0.9457
- val_loss: 0.1009 - val_acc: 0.9699
Epoch 4/20
60000/60000 [==============================] - 3s 49us/step - loss: 0.1653 - acc: 0.9517
- val_loss: 0.0946 - val_acc: 0.9704
Epoch 5/20
60000/60000 [==============================] - 3s 48us/step - loss: 0.1470 - acc: 0.9568
- val_loss: 0.0860 - val_acc: 0.9743
Epoch 6/20
60000/60000 [==============================] - 3s 49us/step - loss: 0.1327 - acc: 0.9614
- val_loss: 0.0816 - val_acc: 0.9741
Epoch 7/20
60000/60000 [==============================] - 3s 48us/step - loss: 0.1190 - acc: 0.9655
- val_loss: 0.0778 - val_acc: 0.9763
Epoch 8/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.1144 - acc: 0.9663
- val_loss: 0.0796 - val_acc: 0.9767
Epoch 9/20
60000/60000 [==============================] - 3s 48us/step - loss: 0.1060 - acc: 0.9682
- val_loss: 0.0748 - val_acc: 0.9791
Epoch 10/20
60000/60000 [==============================] - 3s 49us/step - loss: 0.1007 - acc: 0.9694
- val_loss: 0.0720 - val_acc: 0.9782
Epoch 11/20
60000/60000 [==============================] - 3s 49us/step - loss: 0.0958 - acc: 0.9709
- val_loss: 0.0708 - val_acc: 0.9783
Epoch 12/20
60000/60000 [==============================] - 3s 48us/step - loss: 0.0920 - acc: 0.9721
- val_loss: 0.0711 - val_acc: 0.9784
Epoch 13/20
60000/60000 [==============================] - 3s 49us/step - loss: 0.0896 - acc: 0.9721
- val_loss: 0.0692 - val_acc: 0.9798
Epoch 14/20
60000/60000 [==============================] - 3s 48us/step - loss: 0.0870 - acc: 0.9730
- val_loss: 0.0687 - val_acc: 0.9798
Epoch 15/20
60000/60000 [==============================] - 3s 48us/step - loss: 0.0833 - acc: 0.9742
- val_loss: 0.0656 - val_acc: 0.9809
Epoch 16/20
60000/60000 [==============================] - 3s 48us/step - loss: 0.0781 - acc: 0.9761
- val_loss: 0.0676 - val_acc: 0.9811
Epoch 17/20
60000/60000 [==============================] - 3s 49us/step - loss: 0.0772 - acc: 0.9762
- val_loss: 0.0688 - val_acc: 0.9808
Epoch 18/20
```

```
60000/60000 [==============================] - 3s 49us/step - loss: 0.0745 - acc: 0.9771
- val_loss: 0.0700 - val_acc: 0.9803
Epoch 19/20
60000/60000 [==============================] - 3s 48us/step - loss: 0.0727 - acc: 0.9773
- val_loss: 0.0688 - val_acc: 0.9811
Epoch 20/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.0698 - acc: 0.9785
- val_loss: 0.0651 - val_acc: 0.9817
```

In [0]:

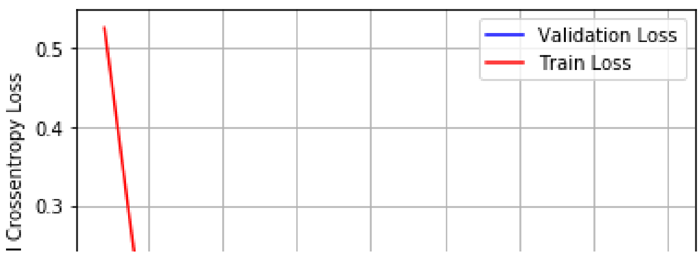
```
model1.summary()
```

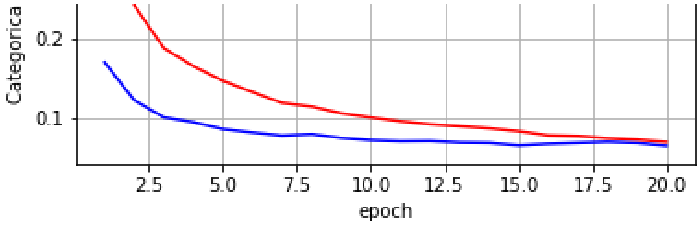
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_8 (Dense)              (None, 256)               200960
_________________________________________________________________
dropout_1 (Dropout)          (None, 256)               0
_________________________________________________________________
dense_9 (Dense)              (None, 128)               32896
_________________________________________________________________
dropout_2 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_10 (Dense)             (None, 10)                1290
=================================================================
Total params: 235,146
Trainable params: 235,146
Non-trainable params: 0
_________________________________________________________________
```

In [0]:

```
score = model1.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

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

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

# print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verb
ose=1, validation_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 epoc
hs

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

```
Test score: 0.06511110941658844
Test accuracy: 0.9817
```

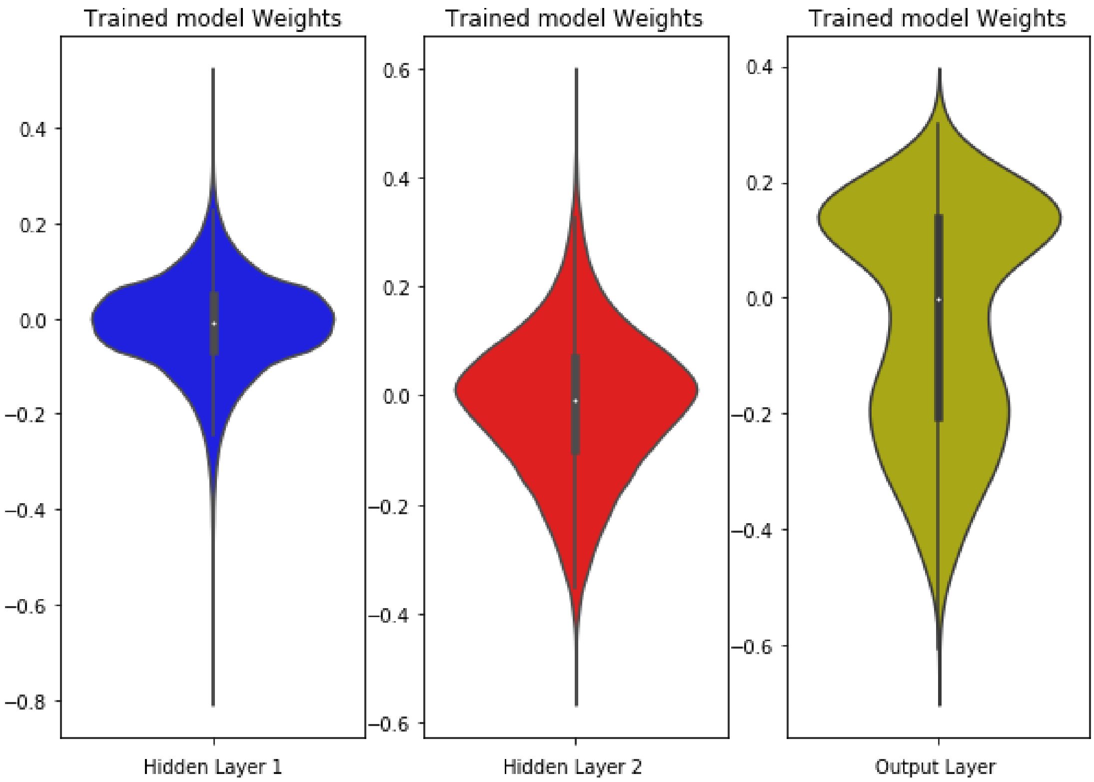




This is so far the best model as both validation and train losses met their minimum values at the 20th epoch

In [0]:

```
w_after = model1.get_weights()

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


fig = plt.figure(figsize=(10,7))
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()
```



1.4 RELU ACTIVATION WITH BATCH NORM

In [0]:

```
from keras.layers.normalization import BatchNormalization
model1 = Sequential()
```

```
model1.add(Dense(256, input_dim=input_dim, activation='relu'))
model1.add(BatchNormalization())
model1.add(Dense(128, input_dim=input_dim, activation='relu'))
model1.add(BatchNormalization())
model1.add(Dense(10, input_dim=input_dim, activation='softmax'))
```

In [0]:

```
model1.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history = model1.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 90us/step - loss: 0.2043 - acc: 0.9397
- val_loss: 0.1063 - val_acc: 0.9658
Epoch 2/20
60000/60000 [==============================] - 5s 78us/step - loss: 0.0804 - acc: 0.9761
- val_loss: 0.0876 - val_acc: 0.9730
Epoch 3/20
60000/60000 [==============================] - 5s 79us/step - loss: 0.0528 - acc: 0.9832
- val_loss: 0.0848 - val_acc: 0.9734
Epoch 4/20
60000/60000 [==============================] - 5s 80us/step - loss: 0.0382 - acc: 0.9881
- val_loss: 0.0808 - val_acc: 0.9757
Epoch 5/20
60000/60000 [==============================] - 5s 81us/step - loss: 0.0290 - acc: 0.9905
- val_loss: 0.0792 - val_acc: 0.9766
Epoch 6/20
60000/60000 [==============================] - 5s 77us/step - loss: 0.0252 - acc: 0.9919
- val_loss: 0.0919 - val_acc: 0.9735
Epoch 7/20
60000/60000 [==============================] - 5s 79us/step - loss: 0.0204 - acc: 0.9932
- val_loss: 0.0706 - val_acc: 0.9791
Epoch 8/20
60000/60000 [==============================] - 5s 81us/step - loss: 0.0170 - acc: 0.9946
- val_loss: 0.0836 - val_acc: 0.9779
Epoch 9/20
60000/60000 [==============================] - 5s 77us/step - loss: 0.0165 - acc: 0.9946
- val_loss: 0.0769 - val_acc: 0.9793
Epoch 10/20
60000/60000 [==============================] - 5s 80us/step - loss: 0.0141 - acc: 0.9952
- val_loss: 0.0873 - val_acc: 0.9769
Epoch 11/20
60000/60000 [==============================] - 5s 79us/step - loss: 0.0126 - acc: 0.9960
- val_loss: 0.0741 - val_acc: 0.9807
Epoch 12/20
60000/60000 [==============================] - 5s 77us/step - loss: 0.0122 - acc: 0.9959
- val_loss: 0.0835 - val_acc: 0.9785
Epoch 13/20
60000/60000 [==============================] - 5s 77us/step - loss: 0.0105 - acc: 0.9963
- val_loss: 0.0873 - val_acc: 0.9779
Epoch 14/20
60000/60000 [==============================] - 5s 77us/step - loss: 0.0112 - acc: 0.9963
- val_loss: 0.0938 - val_acc: 0.9776
Epoch 15/20
60000/60000 [==============================] - 5s 79us/step - loss: 0.0100 - acc: 0.9968
- val_loss: 0.0840 - val_acc: 0.9801
Epoch 16/20
60000/60000 [==============================] - 5s 81us/step - loss: 0.0093 - acc: 0.9968
- val_loss: 0.0808 - val_acc: 0.9813
Epoch 17/20
60000/60000 [==============================] - 5s 76us/step - loss: 0.0099 - acc: 0.9966
- val_loss: 0.0896 - val_acc: 0.9772
Epoch 18/20
60000/60000 [==============================] - 5s 76us/step - loss: 0.0090 - acc: 0.9970
- val_loss: 0.0860 - val_acc: 0.9779
Epoch 19/20
60000/60000 [==============================] - 5s 77us/step - loss: 0.0077 - acc: 0.9972
- val_loss: 0.0824 - val_acc: 0.9799
Epoch 20/20
```

```
60000/60000 [==============================] - 5s 79us/step - loss: 0.0072 - acc: 0.9978
- val_loss: 0.0869 - val_acc: 0.9791
```

In [0]:

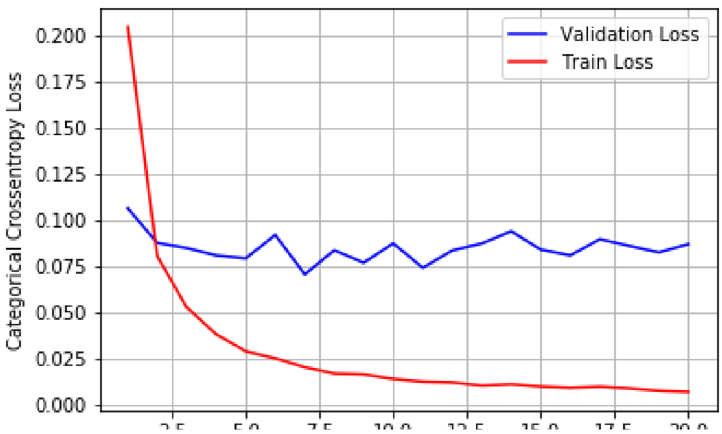
```
model1.summary()
```

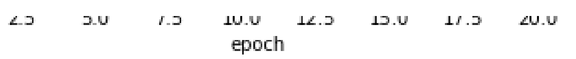
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_11 (Dense)             (None, 256)               200960    
_________________________________________________________________
batch_normalization_1 (Batch (None, 256)               1024      
_________________________________________________________________
dense_12 (Dense)             (None, 128)               32896     
_________________________________________________________________
batch_normalization_2 (Batch (None, 128)               512       
_________________________________________________________________
dense_13 (Dense)             (None, 10)                1290      
=================================================================
Total params: 236,682
Trainable params: 235,914
Non-trainable params: 768
_________________________________________________________________
```

In [0]:

```
score = model1.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

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

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

# print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verb
ose=1, validation_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 epoc
hs

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

```
Test score: 0.08686929494800279
Test accuracy: 0.9791
```

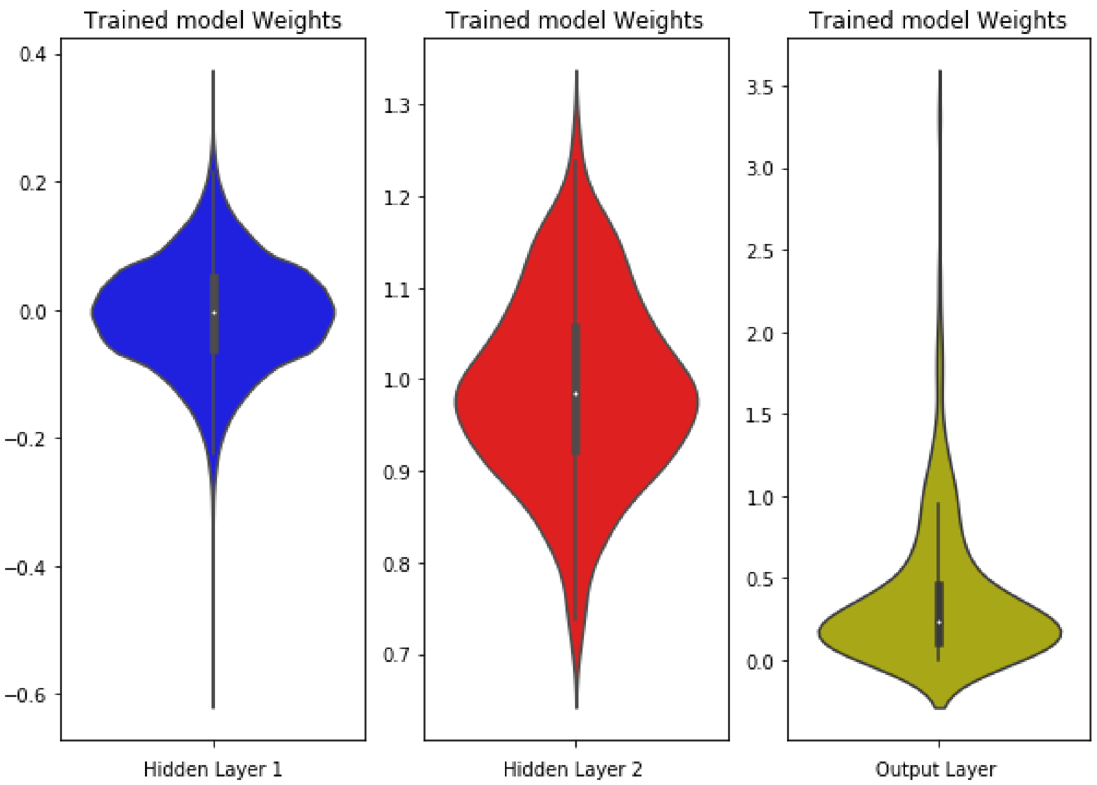




This model was well trained but failed in validation test due to overfitting.

In [0]:

```
w_after = model1.get_weights()

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


fig = plt.figure(figsize=(10,7))
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()
```



1.5 RELU ACTIVATION WITH BATCH NORM AND DROPOUT (0.5)

In [0]:

```
from keras.layers.normalization import BatchNormalization
model1 = Sequential()

model1.add(Dense(256, input_dim=input_dim, activation='relu'))
model1.add(BatchNormalization())
model1.add(Dropout(0.5))

model1.add(Dense(128, input_dim=input_dim, activation='relu'))
```

```
model1.add(BatchNormalization())
model1.add(Dropout(0.5))

model1.add(Dense(10, input_dim=input_dim, activation='softmax'))
```

In [0]:

```
model1.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history = model1.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 [==============================] - 6s 97us/step - loss: 0.4898 - acc: 0.8517
- val_loss: 0.1640 - val_acc: 0.9482
Epoch 2/20
60000/60000 [==============================] - 5s 81us/step - loss: 0.2463 - acc: 0.9267
- val_loss: 0.1271 - val_acc: 0.9610
Epoch 3/20
60000/60000 [==============================] - 5s 81us/step - loss: 0.1993 - acc: 0.9407
- val_loss: 0.1082 - val_acc: 0.9670
Epoch 4/20
60000/60000 [==============================] - 5s 82us/step - loss: 0.1682 - acc: 0.9491
- val_loss: 0.0979 - val_acc: 0.9697
Epoch 5/20
60000/60000 [==============================] - 5s 82us/step - loss: 0.1533 - acc: 0.9545
- val_loss: 0.0899 - val_acc: 0.9727
Epoch 6/20
60000/60000 [==============================] - 5s 79us/step - loss: 0.1376 - acc: 0.9582
- val_loss: 0.0816 - val_acc: 0.9744
Epoch 7/20
60000/60000 [==============================] - 5s 80us/step - loss: 0.1288 - acc: 0.9610
- val_loss: 0.0803 - val_acc: 0.9759
Epoch 8/20
60000/60000 [==============================] - 5s 79us/step - loss: 0.1187 - acc: 0.9636
- val_loss: 0.0761 - val_acc: 0.9768
Epoch 9/20
60000/60000 [==============================] - 5s 80us/step - loss: 0.1104 - acc: 0.9663
- val_loss: 0.0719 - val_acc: 0.9782
Epoch 10/20
60000/60000 [==============================] - 5s 83us/step - loss: 0.1022 - acc: 0.9679
- val_loss: 0.0687 - val_acc: 0.9797
Epoch 11/20
60000/60000 [==============================] - 5s 82us/step - loss: 0.1014 - acc: 0.9691
- val_loss: 0.0727 - val_acc: 0.9775
Epoch 12/20
60000/60000 [==============================] - 5s 81us/step - loss: 0.0991 - acc: 0.9692
- val_loss: 0.0685 - val_acc: 0.9789
Epoch 13/20
60000/60000 [==============================] - 5s 79us/step - loss: 0.0927 - acc: 0.9716
- val_loss: 0.0718 - val_acc: 0.9778
Epoch 14/20
60000/60000 [==============================] - 5s 81us/step - loss: 0.0871 - acc: 0.9731
- val_loss: 0.0659 - val_acc: 0.9799
Epoch 15/20
60000/60000 [==============================] - 5s 80us/step - loss: 0.0868 - acc: 0.9728
- val_loss: 0.0657 - val_acc: 0.9800
Epoch 16/20
60000/60000 [==============================] - 5s 82us/step - loss: 0.0817 - acc: 0.9742
- val_loss: 0.0642 - val_acc: 0.9801
Epoch 17/20
60000/60000 [==============================] - 5s 82us/step - loss: 0.0822 - acc: 0.9747
- val_loss: 0.0659 - val_acc: 0.9807
Epoch 18/20
60000/60000 [==============================] - 5s 79us/step - loss: 0.0752 - acc: 0.9763
- val_loss: 0.0646 - val_acc: 0.9815
Epoch 19/20
60000/60000 [==============================] - 5s 80us/step - loss: 0.0760 - acc: 0.9762
- val_loss: 0.0629 - val_acc: 0.9817
Epoch 20/20
60000/60000 [==============================] - 5s 81us/step - loss: 0.0754 - acc: 0.9763
```

```
- val_loss: 0.0604 - val_acc: 0.9821
```

In [0]:

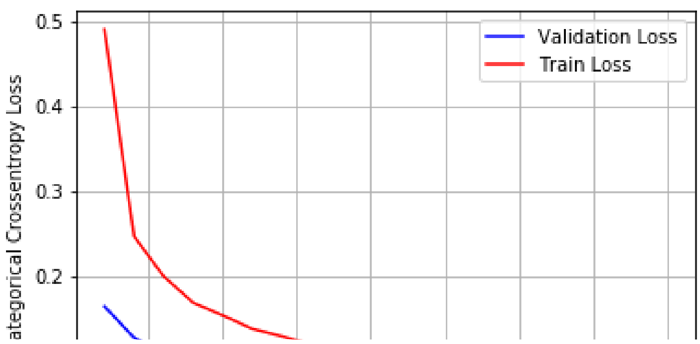
```
model1.summary()
```

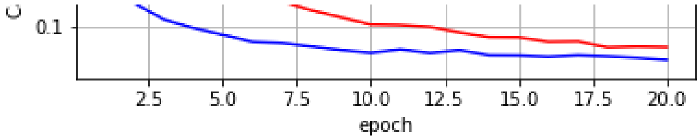
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_15 (Dense)             (None, 256)               200960    
_________________________________________________________________
batch_normalization_4 (Batch (None, 256)               1024      
_________________________________________________________________
dropout_3 (Dropout)          (None, 256)               0         
_________________________________________________________________
dense_16 (Dense)             (None, 128)               32896     
_________________________________________________________________
batch_normalization_5 (Batch (None, 128)               512       
_________________________________________________________________
dropout_4 (Dropout)          (None, 128)               0         
_________________________________________________________________
dense_17 (Dense)             (None, 10)                1290      
=================================================================
Total params: 236,682
Trainable params: 235,914
Non-trainable params: 768
_________________________________________________________________
```

In [0]:

```
score = model1.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

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

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

# print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verb
ose=1, validation_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 epoc
hs

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

```
Test score: 0.06043866992703406
Test accuracy: 0.9821
```

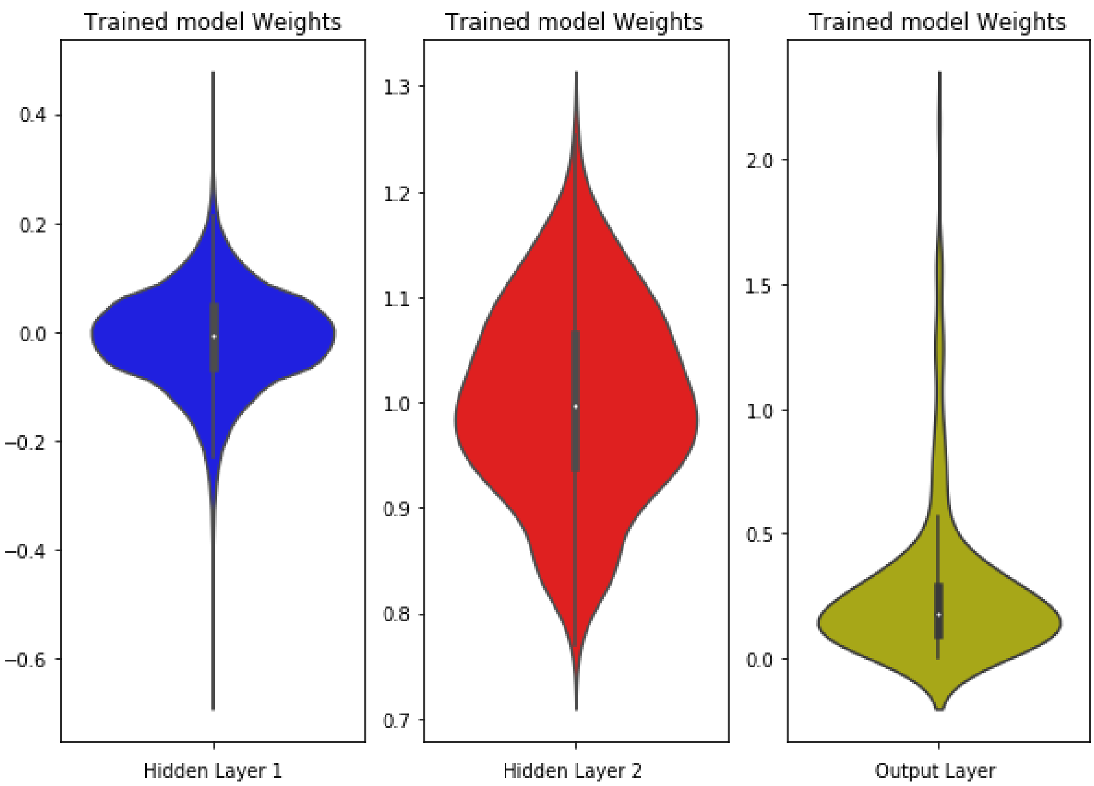




Model is better than others but not upto the model with dropout.

In [0]:

```
w_after = model1.get_weights()

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


fig = plt.figure(figsize=(10,7))
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 - 3 HIDDEN LAYERS

2.1 MODEL WITH 2 POWERS AS NUMBER OF HIDDEN LAYERS (RELU ACTIVATION)

In [0]:

```
model2 = Sequential()
```

```
model2.add(Dense(512, input_dim=input_dim, activation='relu'))
model2.add(Dense(256, input_dim=input_dim, activation='relu'))
model2.add(Dense(128, input_dim=input_dim, activation='relu'))
model2.add(Dense(10, input_dim=input_dim, activation='softmax'))
```

In [0]:

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

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

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 4s 70us/step - loss: 0.2289 - acc: 0.9326
- val_loss: 0.1105 - val_acc: 0.9641
Epoch 2/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.0846 - acc: 0.9738
- val_loss: 0.0812 - val_acc: 0.9746
Epoch 3/20
60000/60000 [==============================] - 3s 58us/step - loss: 0.0536 - acc: 0.9833
- val_loss: 0.0849 - val_acc: 0.9735
Epoch 4/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.0396 - acc: 0.9866
- val_loss: 0.0728 - val_acc: 0.9790
Epoch 5/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.0300 - acc: 0.9900
- val_loss: 0.0752 - val_acc: 0.9786
Epoch 6/20
60000/60000 [==============================] - 3s 58us/step - loss: 0.0241 - acc: 0.9921
- val_loss: 0.0730 - val_acc: 0.9802
Epoch 7/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.0227 - acc: 0.9927
- val_loss: 0.0901 - val_acc: 0.9739
Epoch 8/20
60000/60000 [==============================] - 3s 58us/step - loss: 0.0181 - acc: 0.9943
- val_loss: 0.0865 - val_acc: 0.9785
Epoch 9/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.0186 - acc: 0.9937
- val_loss: 0.0745 - val_acc: 0.9810
Epoch 10/20
60000/60000 [==============================] - 4s 59us/step - loss: 0.0157 - acc: 0.9947
- val_loss: 0.0907 - val_acc: 0.9778
Epoch 11/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.0119 - acc: 0.9960
- val_loss: 0.0836 - val_acc: 0.9809
Epoch 12/20
60000/60000 [==============================] - 4s 60us/step - loss: 0.0139 - acc: 0.9956
- val_loss: 0.0754 - val_acc: 0.9827
Epoch 13/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.0127 - acc: 0.9962
- val_loss: 0.0837 - val_acc: 0.9800
Epoch 14/20
60000/60000 [==============================] - 3s 58us/step - loss: 0.0112 - acc: 0.9964
- val_loss: 0.0921 - val_acc: 0.9808
Epoch 15/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.0124 - acc: 0.9963
- val_loss: 0.0728 - val_acc: 0.9841
Epoch 16/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.0086 - acc: 0.9974
- val_loss: 0.0999 - val_acc: 0.9789
Epoch 17/20
60000/60000 [==============================] - 3s 58us/step - loss: 0.0101 - acc: 0.9969
- val_loss: 0.0962 - val_acc: 0.9799
Epoch 18/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.0079 - acc: 0.9975
- val_loss: 0.0980 - val_acc: 0.9807
Epoch 19/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.0097 - acc: 0.9970
- val_loss: 0.1004 - val_acc: 0.9804
Epoch 20/20
60000/60000 [==============================] - 3s 58us/step - loss: 0.0092 - acc: 0.9975
```

```
- val_loss: 0.1088 - val_acc: 0.9788
```

In [0]:

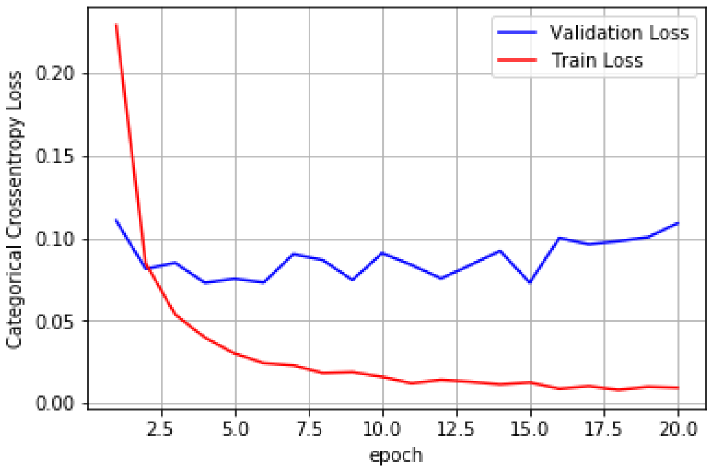
```
model2.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_22 (Dense)             (None, 512)               401920    
_________________________________________________________________
dense_23 (Dense)             (None, 256)               131328    
_________________________________________________________________
dense_24 (Dense)             (None, 128)               32896     
_________________________________________________________________
dense_25 (Dense)             (None, 10)                1290      
=================================================================
Total params: 567,434
Trainable params: 567,434
Non-trainable params: 0
_________________________________________________________________
```

In [0]:

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

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

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

# print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verb
ose=1, validation_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 epoc
hs

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

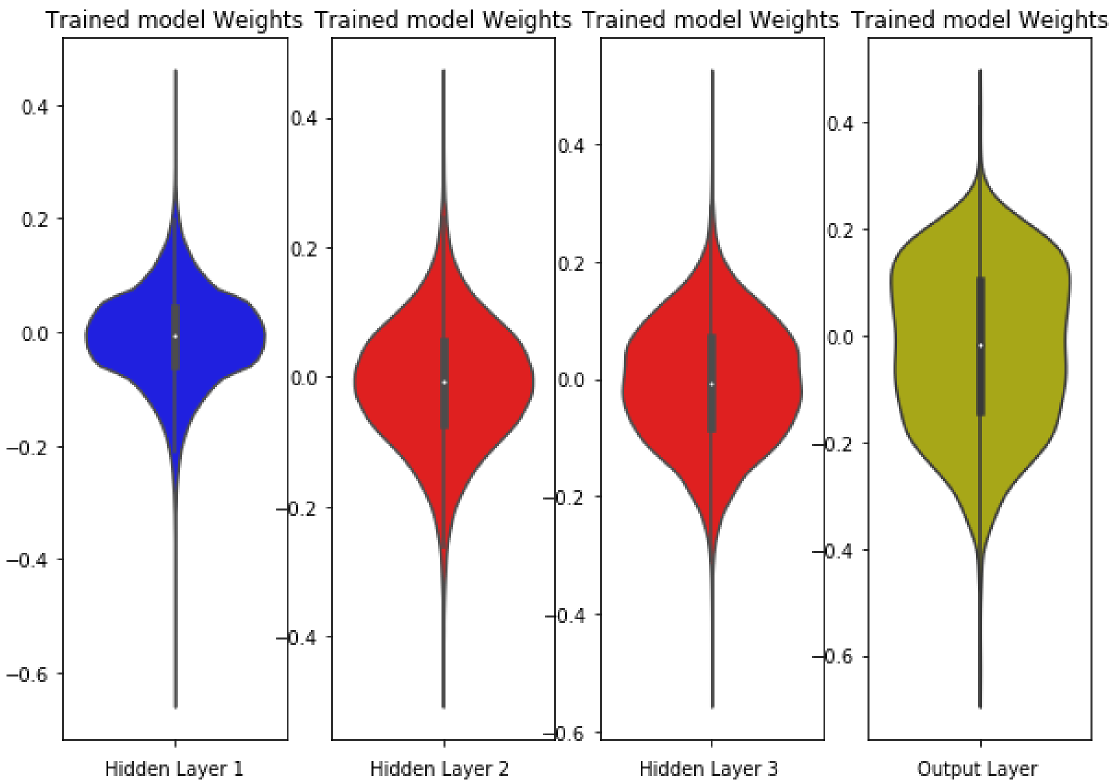
```
Test score: 0.10877159107371262
Test accuracy: 0.9788
```



The model has overfit.

In [0]:

```
w_after = model2.get_weights()

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


fig = plt.figure(figsize=(10,7))
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='r')
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()
```



2.2 RELU ACTIVATION WITH DROPOUT VALUE 0.5

In [0]:

```
from keras.layers import Dropout
model2 = Sequential()
model2.add(Dense(512, input_dim=input_dim, activation='relu'))
model2.add(Dropout(0.5))
model2.add(Dense(256, input_dim=input_dim, activation='relu'))
```

```
model2.add(Dropout(0.5))
model2.add(Dense(128, input_dim=input_dim, activation='relu'))
model2.add(Dropout(0.5))
model2.add(Dense(10, input_dim=input_dim, activation='softmax'))
```

In [0]:

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

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

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 4s 74us/step - loss: 0.5487 - acc: 0.8282
- val_loss: 0.1492 - val_acc: 0.9546
Epoch 2/20
60000/60000 [==============================] - 4s 61us/step - loss: 0.2275 - acc: 0.9369
- val_loss: 0.1108 - val_acc: 0.9671
Epoch 3/20
60000/60000 [==============================] - 4s 60us/step - loss: 0.1762 - acc: 0.9501
- val_loss: 0.0952 - val_acc: 0.9717
Epoch 4/20
60000/60000 [==============================] - 4s 61us/step - loss: 0.1512 - acc: 0.9580
- val_loss: 0.0834 - val_acc: 0.9756
Epoch 5/20
60000/60000 [==============================] - 4s 59us/step - loss: 0.1337 - acc: 0.9623
- val_loss: 0.0789 - val_acc: 0.9776
Epoch 6/20
60000/60000 [==============================] - 4s 59us/step - loss: 0.1204 - acc: 0.9666
- val_loss: 0.0791 - val_acc: 0.9762
Epoch 7/20
60000/60000 [==============================] - 4s 59us/step - loss: 0.1140 - acc: 0.9673
- val_loss: 0.0703 - val_acc: 0.9781
Epoch 8/20
60000/60000 [==============================] - 4s 60us/step - loss: 0.1030 - acc: 0.9716
- val_loss: 0.0697 - val_acc: 0.9805
Epoch 9/20
60000/60000 [==============================] - 4s 59us/step - loss: 0.0950 - acc: 0.9732
- val_loss: 0.0741 - val_acc: 0.9786
Epoch 10/20
60000/60000 [==============================] - 4s 59us/step - loss: 0.0903 - acc: 0.9742
- val_loss: 0.0715 - val_acc: 0.9801
Epoch 11/20
60000/60000 [==============================] - 4s 58us/step - loss: 0.0857 - acc: 0.9755
- val_loss: 0.0719 - val_acc: 0.9792
Epoch 12/20
60000/60000 [==============================] - 4s 60us/step - loss: 0.0837 - acc: 0.9756
- val_loss: 0.0707 - val_acc: 0.9813
Epoch 13/20
60000/60000 [==============================] - 4s 60us/step - loss: 0.0760 - acc: 0.9778
- val_loss: 0.0647 - val_acc: 0.9815
Epoch 14/20
60000/60000 [==============================] - 4s 58us/step - loss: 0.0733 - acc: 0.9781
- val_loss: 0.0718 - val_acc: 0.9815
Epoch 15/20
60000/60000 [==============================] - 4s 61us/step - loss: 0.0715 - acc: 0.9790
- val_loss: 0.0678 - val_acc: 0.9825
Epoch 16/20
60000/60000 [==============================] - 4s 61us/step - loss: 0.0681 - acc: 0.9802
- val_loss: 0.0687 - val_acc: 0.9819
Epoch 17/20
60000/60000 [==============================] - 4s 61us/step - loss: 0.0668 - acc: 0.9808
- val_loss: 0.0671 - val_acc: 0.9822
Epoch 18/20
60000/60000 [==============================] - 4s 61us/step - loss: 0.0650 - acc: 0.9813
- val_loss: 0.0649 - val_acc: 0.9846
Epoch 19/20
60000/60000 [==============================] - 4s 58us/step - loss: 0.0613 - acc: 0.9827
- val_loss: 0.0696 - val_acc: 0.9828
Epoch 20/20
60000/60000 [==============================] - 4s 61us/step - loss: 0.0592 - acc: 0.9823
```

- val_loss: 0.0665 - val_acc: 0.9828

In [0]:

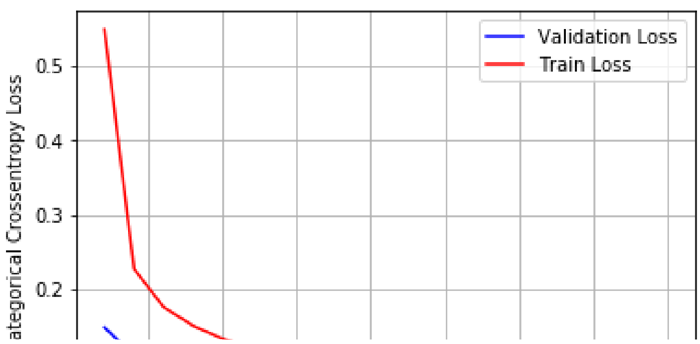
```
model2.summary()
```

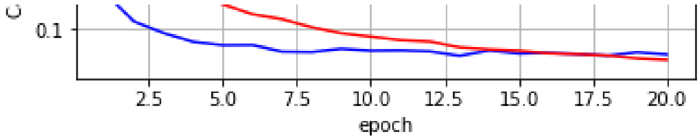
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_26 (Dense)             (None, 512)               401920    
_________________________________________________________________
dropout_5 (Dropout)          (None, 512)               0         
_________________________________________________________________
dense_27 (Dense)             (None, 256)               131328    
_________________________________________________________________
dropout_6 (Dropout)          (None, 256)               0         
_________________________________________________________________
dense_28 (Dense)             (None, 128)               32896     
_________________________________________________________________
dropout_7 (Dropout)          (None, 128)               0         
_________________________________________________________________
dense_29 (Dense)             (None, 10)                1290      
=================================================================
Total params: 567,434
Trainable params: 567,434
Non-trainable params: 0
_________________________________________________________________
```

In [0]:

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

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

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

# print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verb
ose=1, validation_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 epoc
hs

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

```
Test score: 0.06652374192810584
Test accuracy: 0.9828
```

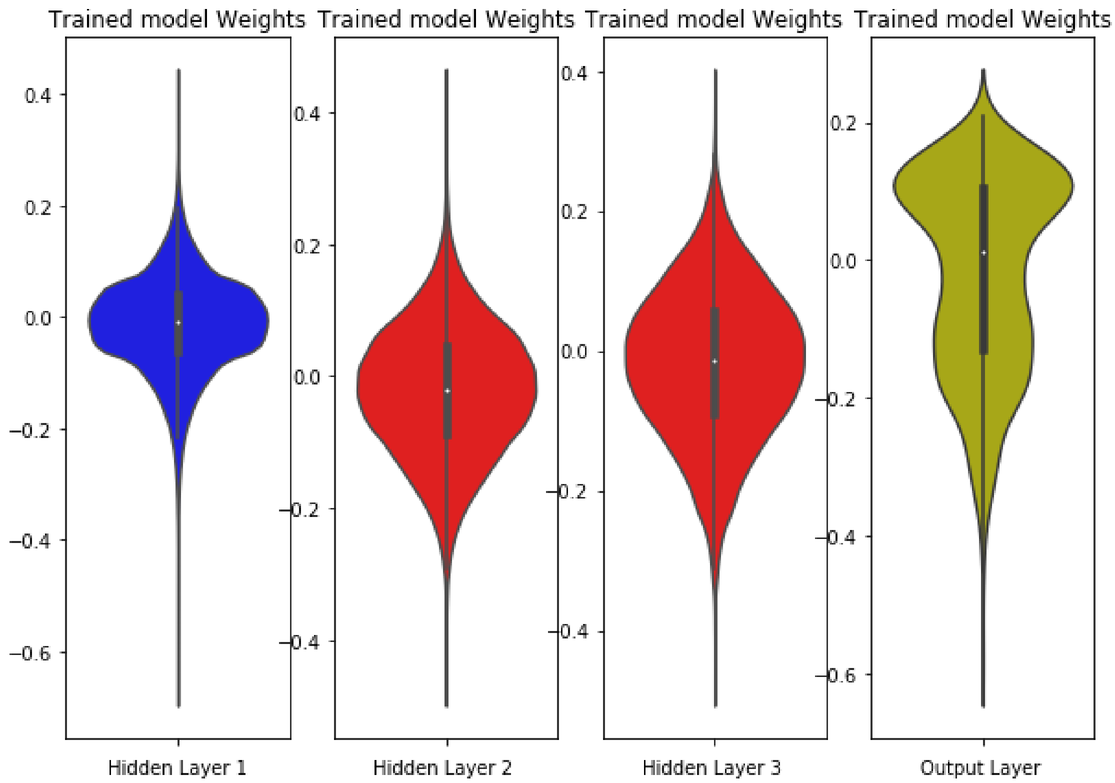




A little overfitting is seen at the final few epochs

In [0]:

```
w_after = model2.get_weights()

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


fig = plt.figure(figsize=(10,7))
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='r')
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()
```



2.3 RELU ACTIVATION WITH BATCH NORM

In [0]:

```
from keras.layers.normalization import BatchNormalization
model2 = Sequential()
model2.add(Dense(512, input_dim=input_dim, activation='relu'))
model2.add(BatchNormalization())
model2.add(Dense(256, input_dim=input_dim, activation='relu'))
model2.add(BatchNormalization())
model2.add(Dense(128, input_dim=input_dim, activation='relu'))
model2.add(BatchNormalization())
model2.add(Dense(10, input_dim=input_dim, activation='softmax'))
```

In [0]:

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

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

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 8s 129us/step - loss: 0.1770 - acc: 0.9460
- val_loss: 0.1025 - val_acc: 0.9682
Epoch 2/20
60000/60000 [==============================] - 6s 103us/step - loss: 0.0715 - acc: 0.9773
- val_loss: 0.0848 - val_acc: 0.9748
Epoch 3/20
60000/60000 [==============================] - 6s 105us/step - loss: 0.0497 - acc: 0.9844
- val_loss: 0.0970 - val_acc: 0.9728
Epoch 4/20
60000/60000 [==============================] - 6s 104us/step - loss: 0.0378 - acc: 0.9877
- val_loss: 0.0878 - val_acc: 0.9721
Epoch 5/20
60000/60000 [==============================] - 6s 105us/step - loss: 0.0333 - acc: 0.9890
- val_loss: 0.0793 - val_acc: 0.9770
Epoch 6/20
60000/60000 [==============================] - 6s 107us/step - loss: 0.0262 - acc: 0.9915
- val_loss: 0.0706 - val_acc: 0.9801
Epoch 7/20
60000/60000 [==============================] - 6s 104us/step - loss: 0.0219 - acc: 0.9927
- val_loss: 0.0877 - val_acc: 0.9769
Epoch 8/20
60000/60000 [==============================] - 6s 104us/step - loss: 0.0226 - acc: 0.9928
- val_loss: 0.0813 - val_acc: 0.9768
Epoch 9/20
60000/60000 [==============================] - 6s 104us/step - loss: 0.0190 - acc: 0.9939
- val_loss: 0.0721 - val_acc: 0.9801
Epoch 10/20
60000/60000 [==============================] - 6s 101us/step - loss: 0.0157 - acc: 0.9949
- val_loss: 0.0913 - val_acc: 0.9752
Epoch 11/20
60000/60000 [==============================] - 6s 107us/step - loss: 0.0184 - acc: 0.9935
- val_loss: 0.0748 - val_acc: 0.9796
Epoch 12/20
60000/60000 [==============================] - 6s 103us/step - loss: 0.0139 - acc: 0.9949
- val_loss: 0.0770 - val_acc: 0.9796
Epoch 13/20
60000/60000 [==============================] - 6s 102us/step - loss: 0.0152 - acc: 0.9950
- val_loss: 0.0831 - val_acc: 0.9776
Epoch 14/20
60000/60000 [==============================] - 6s 103us/step - loss: 0.0092 - acc: 0.9970
- val_loss: 0.0803 - val_acc: 0.9793
Epoch 15/20
60000/60000 [==============================] - 6s 103us/step - loss: 0.0121 - acc: 0.9960
- val_loss: 0.0987 - val_acc: 0.9769
Epoch 16/20
60000/60000 [==============================] - 6s 104us/step - loss: 0.0144 - acc: 0.9954
- val_loss: 0.0833 - val_acc: 0.9799
Epoch 17/20
60000/60000 [==============================] - 6s 105us/step - loss: 0.0109 - acc: 0.9965
- val_loss: 0.0763 - val_acc: 0.9806
Epoch 18/20
60000/60000 [==============================] - 6s 103us/step - loss: 0.0123 - acc: 0.9956
```

```
- val_loss: 0.0705 - val_acc: 0.9829
Epoch 19/20
60000/60000 [==============================] - 6s 103us/step - loss: 0.0079 - acc: 0.9974
- val_loss: 0.0833 - val_acc: 0.9812
Epoch 20/20
60000/60000 [==============================] - 6s 104us/step - loss: 0.0066 - acc: 0.9980
- val_loss: 0.0720 - val_acc: 0.9837
```

In [0]:

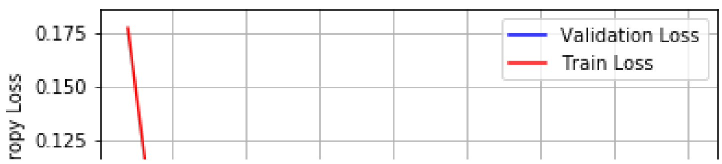
```
model2.summary()
```

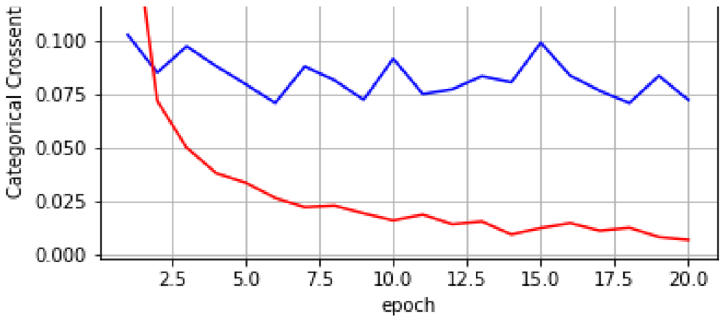
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_30 (Dense)             (None, 512)               401920
_________________________________________________________________
batch_normalization_6 (Batch (None, 512)               2048
_________________________________________________________________
dense_31 (Dense)             (None, 256)               131328
_________________________________________________________________
batch_normalization_7 (Batch (None, 256)               1024
_________________________________________________________________
dense_32 (Dense)             (None, 128)               32896
_________________________________________________________________
batch_normalization_8 (Batch (None, 128)               512
_________________________________________________________________
dense_33 (Dense)             (None, 10)                1290
=================================================================
Total params: 571,018
Trainable params: 569,226
Non-trainable params: 1,792
_________________________________________________________________
```

In [0]:

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

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

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

# print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verb
ose=1, validation_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 epoc
hs

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

```
Test score: 0.07200342553501614
Test accuracy: 0.9837
```

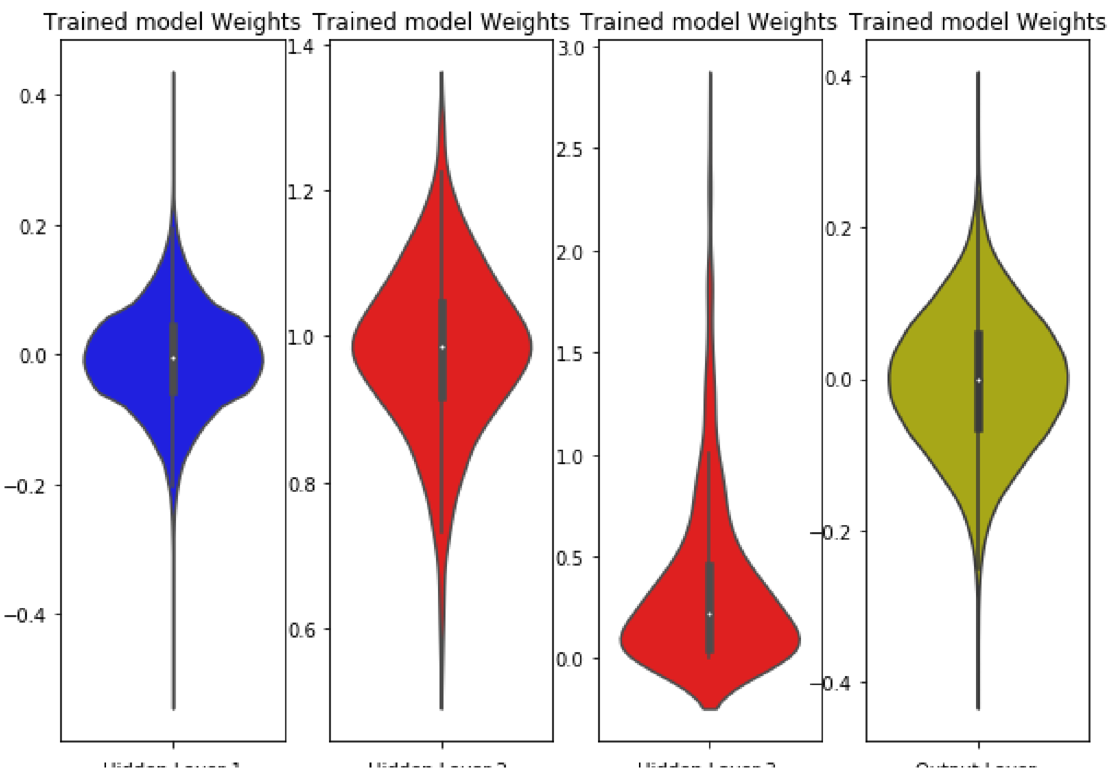




Again overfitting has occured

In [0]:

```
w_after = model2.get_weights()

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


fig = plt.figure(figsize=(10,7))
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='r')
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()
```



Hidden Layer 1 Hidden Layer 2 Hidden Layer 3 Output Layer

2.4 RELU ACTIVATION WITH BATCH NORM AND DROPOUT (0.5)

In [0]:

```python
from keras.layers.normalization import BatchNormalization
model2 = Sequential()

model2.add(Dense(512, input_dim=input_dim, activation='relu'))
model2.add(BatchNormalization())
model2.add(Dropout(0.5))

model2.add(Dense(256, input_dim=input_dim, activation='relu'))
model2.add(BatchNormalization())
model2.add(Dropout(0.5))

model2.add(Dense(128, input_dim=input_dim, activation='relu'))
model2.add(BatchNormalization())
model2.add(Dropout(0.5))

model2.add(Dense(10, input_dim=input_dim, activation='softmax'))
```

In [0]:

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

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

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 8s 139us/step - loss: 0.5245 - acc: 0.8400
- val_loss: 0.1583 - val_acc: 0.9524
Epoch 2/20
60000/60000 [==============================] - 7s 110us/step - loss: 0.2361 - acc: 0.9308
- val_loss: 0.1084 - val_acc: 0.9665
Epoch 3/20
60000/60000 [==============================] - 6s 107us/step - loss: 0.1844 - acc: 0.9447
- val_loss: 0.0976 - val_acc: 0.9702
Epoch 4/20
60000/60000 [==============================] - 6s 108us/step - loss: 0.1586 - acc: 0.9538
- val_loss: 0.0869 - val_acc: 0.9738
Epoch 5/20
60000/60000 [==============================] - 7s 109us/step - loss: 0.1410 - acc: 0.9583
- val_loss: 0.0880 - val_acc: 0.9741
Epoch 6/20
60000/60000 [==============================] - 7s 109us/step - loss: 0.1284 - acc: 0.9615
- val_loss: 0.0775 - val_acc: 0.9756
Epoch 7/20
60000/60000 [==============================] - 6s 107us/step - loss: 0.1172 - acc: 0.9647
- val_loss: 0.0731 - val_acc: 0.9770
Epoch 8/20
60000/60000 [==============================] - 7s 111us/step - loss: 0.1089 - acc: 0.9678
- val_loss: 0.0630 - val_acc: 0.9823
Epoch 9/20
60000/60000 [==============================] - 7s 109us/step - loss: 0.1009 - acc: 0.9699
- val_loss: 0.0660 - val_acc: 0.9812
Epoch 10/20
60000/60000 [==============================] - 7s 109us/step - loss: 0.0976 - acc: 0.9708
- val_loss: 0.0692 - val_acc: 0.9803
Epoch 11/20
60000/60000 [==============================] - 6s 107us/step - loss: 0.0904 - acc: 0.9725
- val_loss: 0.0674 - val_acc: 0.9810
Epoch 12/20
60000/60000 [==============================] - 6s 108us/step - loss: 0.0887 - acc: 0.9731
- val_loss: 0.0657 - val_acc: 0.9804
Epoch 13/20
60000/60000 [==============================] - 7s 110us/step - loss: 0.0816 - acc: 0.9749
- val_loss: 0.0664 - val_acc: 0.9812
Epoch 14/20
60000/60000 [==============================] - 6s 106us/step - loss: 0.0801 - acc: 0.9754
```

```
60000/60000 [==============================] - 6s 106us/step - loss: 0.0801 - acc: 0.9754
- val_loss: 0.0564 - val_acc: 0.9831
Epoch 15/20
60000/60000 [==============================] - 7s 110us/step - loss: 0.0749 - acc: 0.9774
- val_loss: 0.0570 - val_acc: 0.9837
Epoch 16/20
60000/60000 [==============================] - 7s 112us/step - loss: 0.0706 - acc: 0.9784
- val_loss: 0.0624 - val_acc: 0.9816
Epoch 17/20
60000/60000 [==============================] - 6s 108us/step - loss: 0.0727 - acc: 0.9782
- val_loss: 0.0621 - val_acc: 0.9835
Epoch 18/20
60000/60000 [==============================] - 6s 107us/step - loss: 0.0691 - acc: 0.9781
- val_loss: 0.0628 - val_acc: 0.9822
Epoch 19/20
60000/60000 [==============================] - 7s 109us/step - loss: 0.0636 - acc: 0.9801
- val_loss: 0.0622 - val_acc: 0.9824
Epoch 20/20
60000/60000 [==============================] - 7s 110us/step - loss: 0.0632 - acc: 0.9803
- val_loss: 0.0571 - val_acc: 0.9844
```

In [0]:

```
model2.summary()
```

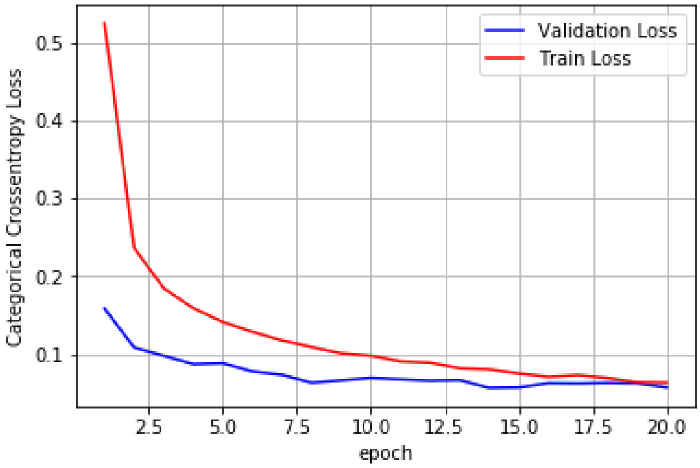
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_38 (Dense)             (None, 512)               401920    
_________________________________________________________________
batch_normalization_12 (Batc (None, 512)               2048      
_________________________________________________________________
dropout_11 (Dropout)         (None, 512)               0         
_________________________________________________________________
dense_39 (Dense)             (None, 256)               131328    
_________________________________________________________________
batch_normalization_13 (Batc (None, 256)               1024      
_________________________________________________________________
dropout_12 (Dropout)         (None, 256)               0         
_________________________________________________________________
dense_40 (Dense)             (None, 128)               32896     
_________________________________________________________________
batch_normalization_14 (Batc (None, 128)               512       
_________________________________________________________________
dropout_13 (Dropout)         (None, 128)               0         
_________________________________________________________________
dense_41 (Dense)             (None, 10)                1290      
=================================================================
Total params: 571,018
Trainable params: 569,226
Non-trainable params: 1,792
_________________________________________________________________
```

In [0]:

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

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

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

# print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verb
ose=1, validation_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 epoc
hs

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

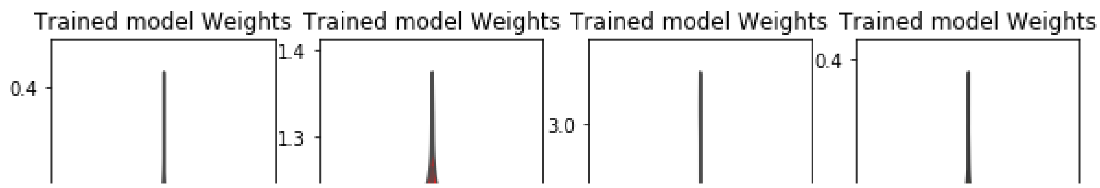
```
Test score: 0.05705453945930348 5
Test accuracy: 0.9844
```

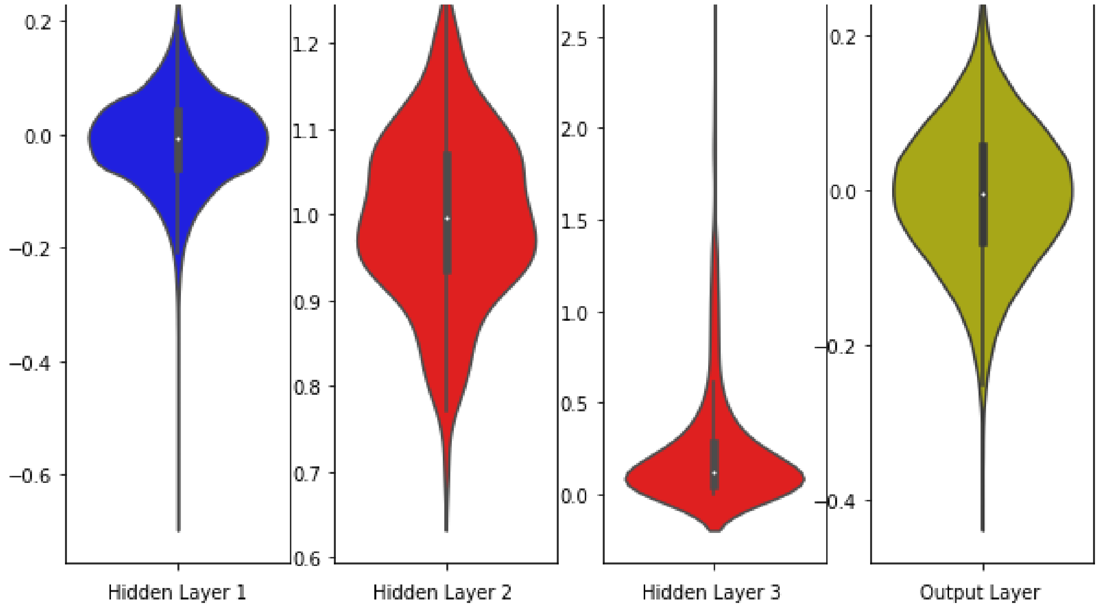


The best model in 3 hidden layer models.

In [0]:

```
w_after = model2.get_weights()

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


fig = plt.figure(figsize=(10,7))
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='r')
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 - 5 HIDDEN LAYERS

3.1 MODEL WITH 2 POWERS AS NUMBER OF HIDDEN LAYERS (RELU ACTIVATION)

In [0]:

```
model3 = Sequential()
model3.add(Dense(512, input_dim=input_dim, activation='relu'))
model3.add(Dense(256, input_dim=input_dim, activation='relu'))
model3.add(Dense(128, input_dim=input_dim, activation='relu'))
model3.add(Dense(64, input_dim=input_dim, activation='relu'))
model3.add(Dense(10, input_dim=input_dim, activation='softmax'))
```

In [0]:

```
model3.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history = model3.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 85us/step - loss: 0.2399 - acc: 0.9279
- val_loss: 0.1218 - val_acc: 0.9621
Epoch 2/20
60000/60000 [==============================] - 4s 63us/step - loss: 0.0875 - acc: 0.9728
- val_loss: 0.0844 - val_acc: 0.9743
Epoch 3/20
60000/60000 [==============================] - 4s 62us/step - loss: 0.0589 - acc: 0.9813
- val_loss: 0.0850 - val_acc: 0.9735
Epoch 4/20
60000/60000 [==============================] - 4s 63us/step - loss: 0.0432 - acc: 0.9866
- val_loss: 0.0687 - val_acc: 0.9798
Epoch 5/20
60000/60000 [==============================] - 4s 62us/step - loss: 0.0329 - acc: 0.9889
- val_loss: 0.0798 - val_acc: 0.9769
Epoch 6/20
60000/60000 [==============================] - 4s 61us/step - loss: 0.0307 - acc: 0.9899
- val_loss: 0.0676 - val_acc: 0.9804
Epoch 7/20
60000/60000 [==============================] - 4s 61us/step - loss: 0.0249 - acc: 0.9920
- val_loss: 0.0768 - val_acc: 0.9802
Epoch 8/20
60000/60000 [==============================] - 4s 61us/step - loss: 0.0216 - acc: 0.9931
- val_loss: 0.0796 - val_acc: 0.9792
Epoch 9/20
60000/60000 [==============================] - 4s 62us/step - loss: 0.0197 - acc: 0.9935
- val_loss: 0.0846 - val_acc: 0.9796
Epoch 10/20
```

```
Epoch 10/20
60000/60000 [==============================] - 4s 63us/step - loss: 0.0177 - acc: 0.9940
- val_loss: 0.0771 - val_acc: 0.9803
Epoch 11/20
60000/60000 [==============================] - 4s 62us/step - loss: 0.0142 - acc: 0.9955
- val_loss: 0.0869 - val_acc: 0.9793
Epoch 12/20
60000/60000 [==============================] - 4s 63us/step - loss: 0.0160 - acc: 0.9951
- val_loss: 0.0756 - val_acc: 0.9815
Epoch 13/20
60000/60000 [==============================] - 4s 63us/step - loss: 0.0145 - acc: 0.9955
- val_loss: 0.0874 - val_acc: 0.9786
Epoch 14/20
60000/60000 [==============================] - 4s 62us/step - loss: 0.0124 - acc: 0.9960
- val_loss: 0.0932 - val_acc: 0.9793
Epoch 15/20
60000/60000 [==============================] - 4s 62us/step - loss: 0.0129 - acc: 0.9960
- val_loss: 0.0936 - val_acc: 0.9807
Epoch 16/20
60000/60000 [==============================] - 4s 62us/step - loss: 0.0115 - acc: 0.9963
- val_loss: 0.0906 - val_acc: 0.9785
Epoch 17/20
60000/60000 [==============================] - 4s 62us/step - loss: 0.0088 - acc: 0.9974
- val_loss: 0.1056 - val_acc: 0.9775
Epoch 18/20
60000/60000 [==============================] - 4s 63us/step - loss: 0.0135 - acc: 0.9957
- val_loss: 0.0892 - val_acc: 0.9811
Epoch 19/20
60000/60000 [==============================] - 4s 62us/step - loss: 0.0072 - acc: 0.9979
- val_loss: 0.1064 - val_acc: 0.9784
Epoch 20/20
60000/60000 [==============================] - 4s 62us/step - loss: 0.0112 - acc: 0.9965
- val_loss: 0.0849 - val_acc: 0.9813
```

In [0]:

```
model3.summary()
```

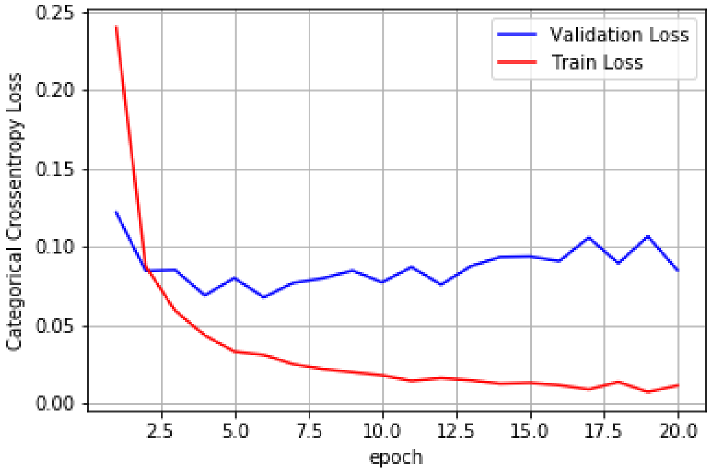
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_42 (Dense)             (None, 512)               401920    
_________________________________________________________________
dense_43 (Dense)             (None, 256)               131328    
_________________________________________________________________
dense_44 (Dense)             (None, 128)               32896     
_________________________________________________________________
dense_45 (Dense)             (None, 64)                8256      
_________________________________________________________________
dense_46 (Dense)             (None, 10)                650       
=================================================================
Total params: 575,050
Trainable params: 575,050
Non-trainable params: 0
_________________________________________________________________
```

In [0]:

```
score = model3.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

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

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

# print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verb
ose=1, validation_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 epoc
hs

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

```
Test score: 0.08486868686463067
Test accuracy: 0.9813
```

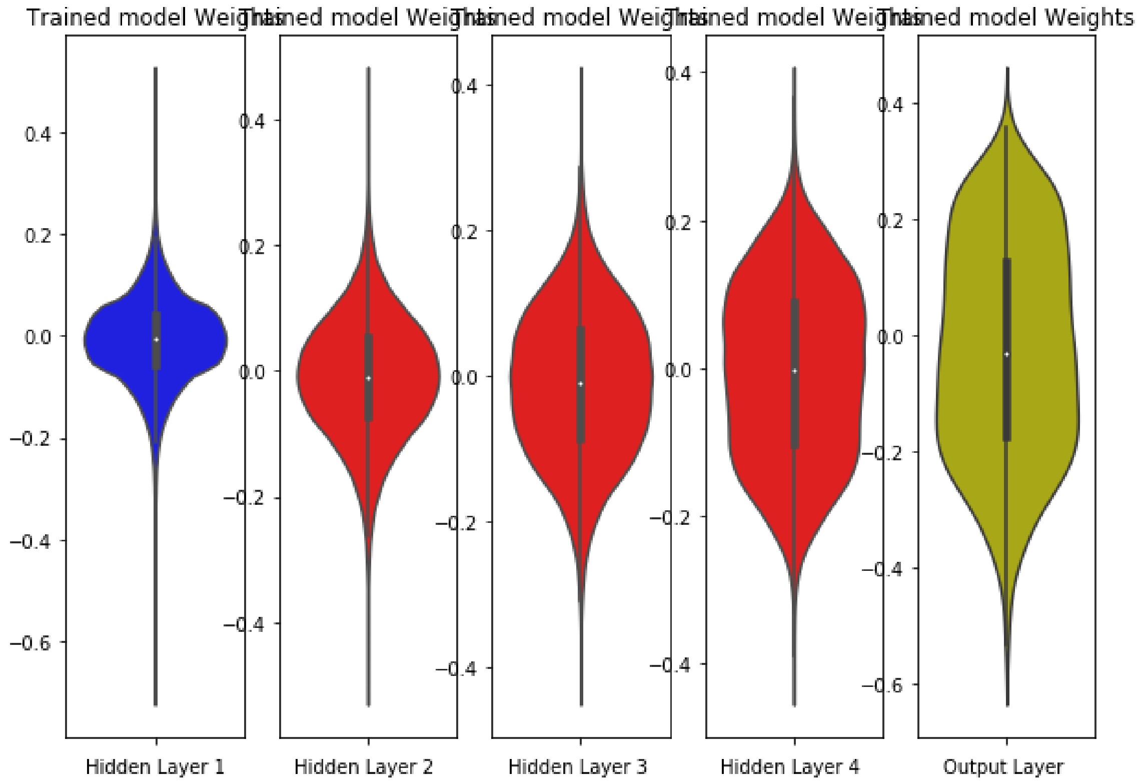


Overfitting is observed.

In [0]:

```
w_after = model3.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)
out_w = w_after[8].flatten().reshape(-1,1)


fig = plt.figure(figsize=(10,7))
plt.title("Weight matrices after model trained")
plt.subplot(1, 5, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

plt.subplot(1, 5, 2)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden Layer 2 ')

plt.subplot(1, 5, 3)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h3_w, color='r')
plt.xlabel('Hidden Layer 3 ')

plt.subplot(1, 5, 4)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h4_w, color='r')
plt.xlabel('Hidden Layer 4 ')

plt.subplot(1, 5, 5)
plt.title("Trained model Weights")
```

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



3.2 RELU ACTIVATION WITH DROPOUT VALUE 0.5

In [0]:

```
from keras.layers import Dropout
model3 = Sequential()
model3.add(Dense(512, input_dim=input_dim, activation='relu'))
model3.add(Dropout(0.5))
model3.add(Dense(256, input_dim=input_dim, activation='relu'))
model3.add(Dropout(0.5))
model3.add(Dense(128, input_dim=input_dim, activation='relu'))
model3.add(Dropout(0.5))
model3.add(Dense(64, input_dim=input_dim, activation='relu'))
model3.add(Dropout(0.5))
model3.add(Dense(10, input_dim=input_dim, activation='softmax'))
```

In [0]:

```
model3.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history = model3.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 [==============================] - 6s 95us/step - loss: 0.8366 - acc: 0.7285
- val_loss: 0.2140 - val_acc: 0.9408
Epoch 2/20
60000/60000 [==============================] - 4s 65us/step - loss: 0.3213 - acc: 0.9203
- val_loss: 0.1466 - val_acc: 0.9608
Epoch 3/20
60000/60000 [==============================] - 4s 66us/step - loss: 0.2444 - acc: 0.9390
- val_loss: 0.1272 - val_acc: 0.9682
Epoch 4/20
60000/60000 [==============================] - 4s 65us/step - loss: 0.2060 - acc: 0.9502
- val_loss: 0.1079 - val_acc: 0.9716
Epoch 5/20
60000/60000 [==============================] - 4s 66us/step - loss: 0.1863 - acc: 0.9544
- val_loss: 0.1049 - val_acc: 0.9723
Epoch 6/20
60000/60000 [==============================] - 4s 67us/step - loss: 0.1709 - acc: 0.9578
```

```
- val_loss: 0.1066 - val_acc: 0.9739
Epoch 7/20
60000/60000 [==============================] - 4s 66us/step - loss: 0.1585 - acc: 0.9613
- val_loss: 0.1017 - val_acc: 0.9738
Epoch 8/20
60000/60000 [==============================] - 4s 67us/step - loss: 0.1455 - acc: 0.9637
- val_loss: 0.0901 - val_acc: 0.9760
Epoch 9/20
60000/60000 [==============================] - 4s 66us/step - loss: 0.1379 - acc: 0.9660
- val_loss: 0.0914 - val_acc: 0.9772
Epoch 10/20
60000/60000 [==============================] - 4s 68us/step - loss: 0.1343 - acc: 0.9676
- val_loss: 0.0839 - val_acc: 0.9777
Epoch 11/20
60000/60000 [==============================] - 4s 66us/step - loss: 0.1212 - acc: 0.9697
- val_loss: 0.0862 - val_acc: 0.9787
Epoch 12/20
60000/60000 [==============================] - 4s 66us/step - loss: 0.1175 - acc: 0.9718
- val_loss: 0.0805 - val_acc: 0.9799
Epoch 13/20
60000/60000 [==============================] - 4s 66us/step - loss: 0.1113 - acc: 0.9734
- val_loss: 0.0878 - val_acc: 0.9772
Epoch 14/20
60000/60000 [==============================] - 4s 65us/step - loss: 0.1093 - acc: 0.9728
- val_loss: 0.0852 - val_acc: 0.9789
Epoch 15/20
60000/60000 [==============================] - 4s 67us/step - loss: 0.1058 - acc: 0.9742
- val_loss: 0.0893 - val_acc: 0.9791
Epoch 16/20
60000/60000 [==============================] - 4s 67us/step - loss: 0.1044 - acc: 0.9741
- val_loss: 0.0881 - val_acc: 0.9792
Epoch 17/20
60000/60000 [==============================] - 4s 66us/step - loss: 0.0997 - acc: 0.9752
- val_loss: 0.0779 - val_acc: 0.9807
Epoch 18/20
60000/60000 [==============================] - 4s 67us/step - loss: 0.0953 - acc: 0.9756
- val_loss: 0.0801 - val_acc: 0.9814
Epoch 19/20
60000/60000 [==============================] - 4s 66us/step - loss: 0.0911 - acc: 0.9772
- val_loss: 0.0870 - val_acc: 0.9812
Epoch 20/20
60000/60000 [==============================] - 4s 66us/step - loss: 0.0961 - acc: 0.9763
- val_loss: 0.0736 - val_acc: 0.9820
```

In [0]:

```
model3.summary()
```

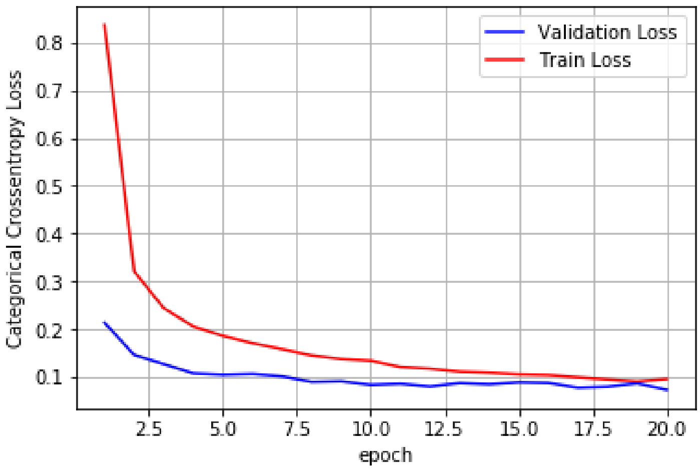
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_47 (Dense)             (None, 512)               401920    
_________________________________________________________________
dropout_14 (Dropout)         (None, 512)               0         
_________________________________________________________________
dense_48 (Dense)             (None, 256)               131328    
_________________________________________________________________
dropout_15 (Dropout)         (None, 256)               0         
_________________________________________________________________
dense_49 (Dense)             (None, 128)               32896     
_________________________________________________________________
dropout_16 (Dropout)         (None, 128)               0         
_________________________________________________________________
dense_50 (Dense)             (None, 64)                8256      
_________________________________________________________________
dropout_17 (Dropout)         (None, 64)                0         
_________________________________________________________________
dense_51 (Dense)             (None, 10)                650       
=================================================================
Total params: 575,050
Trainable params: 575,050
Non-trainable params: 0
```

```
Non-trainable params: 0
_________________________________________________________________
```

In [0]:

```
score = model3.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

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

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

# print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verb
ose=1, validation_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 epoc
hs

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

```
Test score: 0.07358933680157234
Test accuracy: 0.982
```

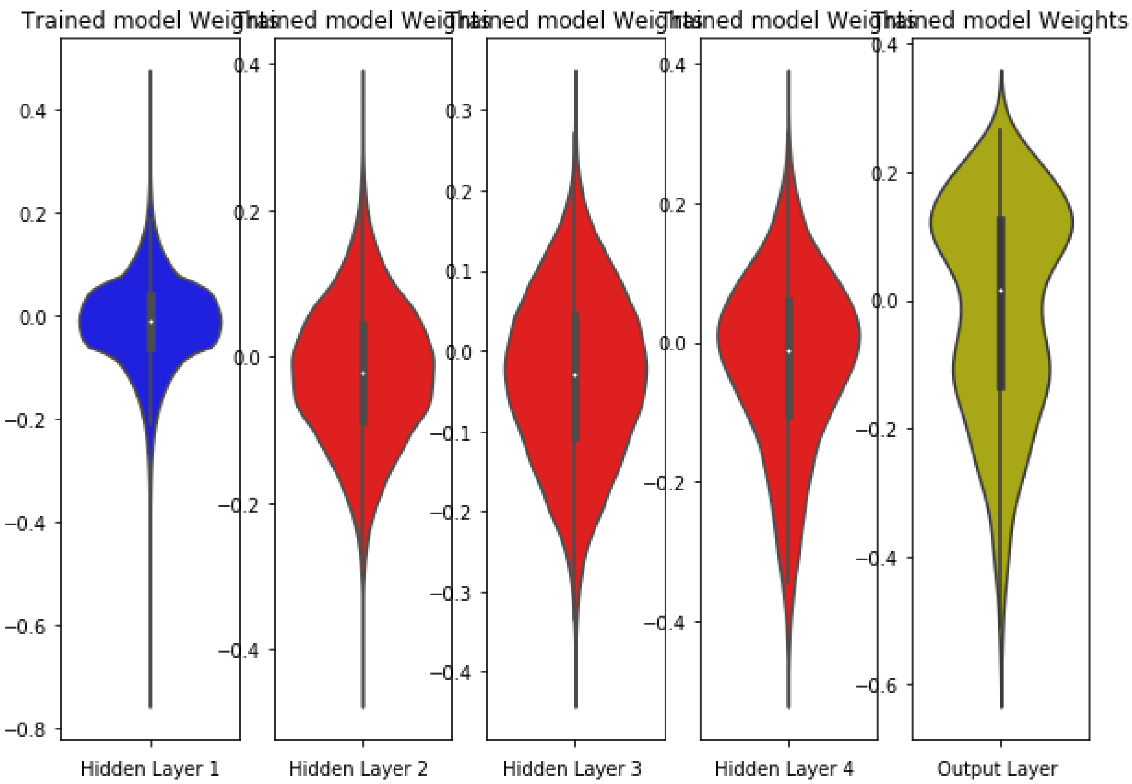


The best model in 5 hidden layer models.

In [0]:

```
w_after = model3.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)
out_w = w_after[8].flatten().reshape(-1,1)


fig = plt.figure(figsize=(10,7))
plt.title("Weight matrices after model trained")
plt.subplot(1, 5, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')
```

```
plt.subplot(1, 5, 2)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden Layer 2 ')

plt.subplot(1, 5, 3)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h3_w, color='r')
plt.xlabel('Hidden Layer 3 ')

plt.subplot(1, 5, 4)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h4_w, color='r')
plt.xlabel('Hidden Layer 4 ')

plt.subplot(1, 5, 5)
plt.title("Trained model Weights")
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output Layer ')
plt.show()
```



3.3 RELU ACTIVATION WITH BATCH NORM

In [0]:

```
from keras.layers.normalization import BatchNormalization
model3 = Sequential()
model3.add(Dense(512, input_dim=input_dim, activation='relu'))
model3.add(BatchNormalization())
model3.add(Dense(256, input_dim=input_dim, activation='relu'))
model3.add(BatchNormalization())
model3.add(Dense(128, input_dim=input_dim, activation='relu'))
model3.add(BatchNormalization())
model3.add(Dense(64, input_dim=input_dim, activation='relu'))
model3.add(BatchNormalization())
model3.add(Dense(10, input_dim=input_dim, activation='softmax'))
```

In [0]:

```
model3.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history = model3.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 [==============================] - 10s 162us/step - loss: 0.2005 - acc: 0.940
7 - val_loss: 0.0970 - val_acc: 0.9689
Epoch 2/20
60000/60000 [==============================] - 7s 124us/step - loss: 0.0809 - acc: 0.9753
- val_loss: 0.1065 - val_acc: 0.9652
Epoch 3/20
60000/60000 [==============================] - 8s 126us/step - loss: 0.0576 - acc: 0.9820
- val_loss: 0.1053 - val_acc: 0.9676
Epoch 4/20
60000/60000 [==============================] - 8s 127us/step - loss: 0.0441 - acc: 0.9858
- val_loss: 0.0779 - val_acc: 0.9763
Epoch 5/20
60000/60000 [==============================] - 7s 122us/step - loss: 0.0354 - acc: 0.9886
- val_loss: 0.0798 - val_acc: 0.9771
Epoch 6/20
60000/60000 [==============================] - 8s 126us/step - loss: 0.0313 - acc: 0.9899
- val_loss: 0.0671 - val_acc: 0.9819
Epoch 7/20
60000/60000 [==============================] - 7s 122us/step - loss: 0.0272 - acc: 0.9911
- val_loss: 0.0701 - val_acc: 0.9792
Epoch 8/20
60000/60000 [==============================] - 7s 123us/step - loss: 0.0254 - acc: 0.9913
- val_loss: 0.0842 - val_acc: 0.9780
Epoch 9/20
60000/60000 [==============================] - 7s 123us/step - loss: 0.0220 - acc: 0.9925
- val_loss: 0.0711 - val_acc: 0.9792
Epoch 10/20
60000/60000 [==============================] - 7s 123us/step - loss: 0.0212 - acc: 0.9930
- val_loss: 0.0845 - val_acc: 0.9770
Epoch 11/20
60000/60000 [==============================] - 7s 122us/step - loss: 0.0192 - acc: 0.9936
- val_loss: 0.0822 - val_acc: 0.9788
Epoch 12/20
60000/60000 [==============================] - 8s 126us/step - loss: 0.0150 - acc: 0.9952
- val_loss: 0.0762 - val_acc: 0.9803
Epoch 13/20
60000/60000 [==============================] - 7s 121us/step - loss: 0.0172 - acc: 0.9943
- val_loss: 0.0726 - val_acc: 0.9804
Epoch 14/20
60000/60000 [==============================] - 7s 124us/step - loss: 0.0181 - acc: 0.9940
- val_loss: 0.0798 - val_acc: 0.9786
Epoch 15/20
60000/60000 [==============================] - 7s 123us/step - loss: 0.0126 - acc: 0.9957
- val_loss: 0.0720 - val_acc: 0.9809
Epoch 16/20
60000/60000 [==============================] - 8s 127us/step - loss: 0.0119 - acc: 0.9959
- val_loss: 0.0807 - val_acc: 0.9803
Epoch 17/20
60000/60000 [==============================] - 7s 124us/step - loss: 0.0120 - acc: 0.9959
- val_loss: 0.0796 - val_acc: 0.9814
Epoch 18/20
60000/60000 [==============================] - 7s 123us/step - loss: 0.0134 - acc: 0.9955
- val_loss: 0.0792 - val_acc: 0.9802
Epoch 19/20
60000/60000 [==============================] - 7s 124us/step - loss: 0.0104 - acc: 0.9965
- val_loss: 0.0752 - val_acc: 0.9820
Epoch 20/20
60000/60000 [==============================] - 7s 123us/step - loss: 0.0108 - acc: 0.9963
- val_loss: 0.1005 - val_acc: 0.9774
```

In [0]:

```
model3.summary()
```

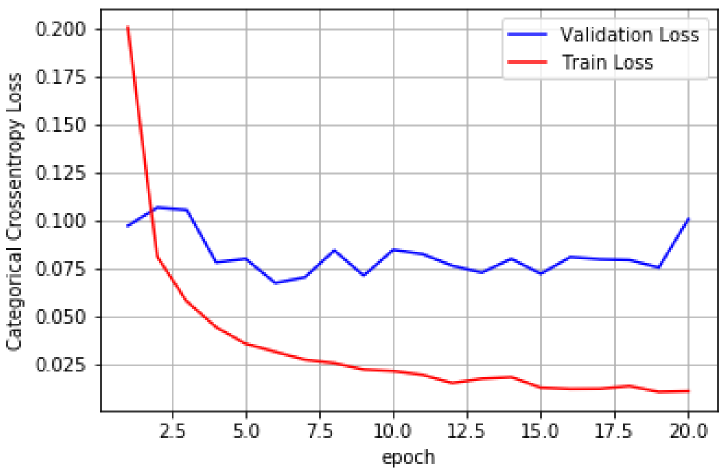
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_52 (Dense)             (None, 512)               401920
_________________________________________________________________
batch_normalization_15 (Batc (None, 512)               2048
```

```
batch_normalization_15 (Batc (None, 512)              2048
_________________________________________________________________
dense_53 (Dense)             (None, 256)              131328
_________________________________________________________________
batch_normalization_16 (Batc (None, 256)              1024
_________________________________________________________________
dense_54 (Dense)             (None, 128)              32896
_________________________________________________________________
batch_normalization_17 (Batc (None, 128)              512
_________________________________________________________________
dense_55 (Dense)             (None, 64)               8256
_________________________________________________________________
batch_normalization_18 (Batc (None, 64)               256
_________________________________________________________________
dense_56 (Dense)             (None, 10)               650
=================================================================
Total params: 578,890
Trainable params: 576,970
Non-trainable params: 1,920
_________________________________________________________________
```

In [0]:

```
score = model3.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

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

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

# print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verb
ose=1, validation_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 epoc
hs

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

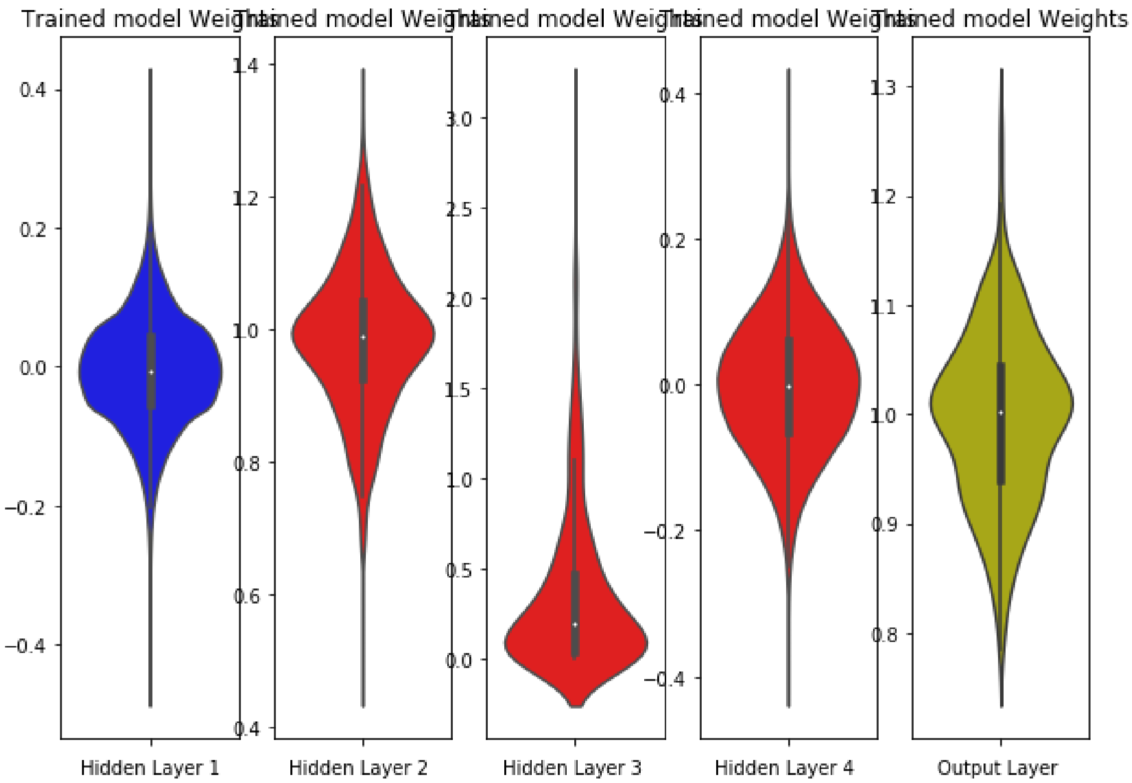
```
Test score: 0.1004731001386419
Test accuracy: 0.9774
```



Overfitting at the very early epochs.

In [0]:

```
w_after = model3.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)
out_w = w_after[8].flatten().reshape(-1,1)


fig = plt.figure(figsize=(10,7))
plt.title("Weight matrices after model trained")
plt.subplot(1, 5, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

plt.subplot(1, 5, 2)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden Layer 2 ')

plt.subplot(1, 5, 3)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h3_w, color='r')
plt.xlabel('Hidden Layer 3 ')

plt.subplot(1, 5, 4)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h4_w, color='r')
plt.xlabel('Hidden Layer 4 ')

plt.subplot(1, 5, 5)
plt.title("Trained model Weights")
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output Layer ')
plt.show()
```



3.4 RELU ACTIVATION WITH BATCH NORM AND DROPOUT (0.5)

In [0]:

```
from keras.layers.normalization import BatchNormalization
```

```
model3 = Sequential()

model3.add(Dense(512, input_dim=input_dim, activation='relu'))
model3.add(BatchNormalization())
model3.add(Dropout(0.5))

model3.add(Dense(256, input_dim=input_dim, activation='relu'))
model3.add(BatchNormalization())
model3.add(Dropout(0.5))

model3.add(Dense(128, input_dim=input_dim, activation='relu'))
model3.add(BatchNormalization())
model3.add(Dropout(0.5))

model3.add(Dense(64, input_dim=input_dim, activation='relu'))
model3.add(BatchNormalization())
model3.add(Dropout(0.5))

model3.add(Dense(10, input_dim=input_dim, activation='softmax'))
```

In [0]:

```
model3.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history = model3.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1
, validation_data=(X_test, Y_test))
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 11s 180us/step - loss: 0.8112 - acc: 0.753
4 - val_loss: 0.2031 - val_acc: 0.9414
Epoch 2/20
60000/60000 [==============================] - 8s 131us/step - loss: 0.3121 - acc: 0.9153
- val_loss: 0.1321 - val_acc: 0.9625
Epoch 3/20
60000/60000 [==============================] - 8s 129us/step - loss: 0.2375 - acc: 0.9369
- val_loss: 0.1194 - val_acc: 0.9650
Epoch 4/20
60000/60000 [==============================] - 8s 129us/step - loss: 0.2027 - acc: 0.9460
- val_loss: 0.1066 - val_acc: 0.9689
Epoch 5/20
60000/60000 [==============================] - 8s 130us/step - loss: 0.1734 - acc: 0.9541
- val_loss: 0.0918 - val_acc: 0.9746
Epoch 6/20
60000/60000 [==============================] - 8s 131us/step - loss: 0.1629 - acc: 0.9556
- val_loss: 0.0926 - val_acc: 0.9748
Epoch 7/20
60000/60000 [==============================] - 8s 128us/step - loss: 0.1523 - acc: 0.9597
- val_loss: 0.0850 - val_acc: 0.9765
Epoch 8/20
60000/60000 [==============================] - 8s 130us/step - loss: 0.1430 - acc: 0.9621
- val_loss: 0.0874 - val_acc: 0.9748
Epoch 9/20
60000/60000 [==============================] - 8s 130us/step - loss: 0.1335 - acc: 0.9647
- val_loss: 0.0760 - val_acc: 0.9789
Epoch 10/20
60000/60000 [==============================] - 8s 131us/step - loss: 0.1239 - acc: 0.9666
- val_loss: 0.0757 - val_acc: 0.9774
Epoch 11/20
60000/60000 [==============================] - 8s 130us/step - loss: 0.1204 - acc: 0.9673
- val_loss: 0.0717 - val_acc: 0.9809
Epoch 12/20
60000/60000 [==============================] - 8s 128us/step - loss: 0.1138 - acc: 0.9685
- val_loss: 0.0737 - val_acc: 0.9812
Epoch 13/20
60000/60000 [==============================] - 8s 133us/step - loss: 0.1081 - acc: 0.9719
- val_loss: 0.0699 - val_acc: 0.9823
Epoch 14/20
60000/60000 [==============================] - 8s 131us/step - loss: 0.1038 - acc: 0.9720
- val_loss: 0.0680 - val_acc: 0.9828
Epoch 15/20
60000/60000 [==============================] - 8s 129us/step - loss: 0.1028 - acc: 0.9718
```

```
- val_loss: 0.0694 - val_acc: 0.9810
Epoch 16/20
60000/60000 [==============================] - 8s 134us/step - loss: 0.0914 - acc: 0.9752
- val_loss: 0.0673 - val_acc: 0.9819
Epoch 17/20
60000/60000 [==============================] - 8s 132us/step - loss: 0.0956 - acc: 0.9747
- val_loss: 0.0631 - val_acc: 0.9829
Epoch 18/20
60000/60000 [==============================] - 8s 130us/step - loss: 0.0907 - acc: 0.9757
- val_loss: 0.0654 - val_acc: 0.9825
Epoch 19/20
60000/60000 [==============================] - 8s 130us/step - loss: 0.0867 - acc: 0.9762
- val_loss: 0.0676 - val_acc: 0.9827
Epoch 20/20
60000/60000 [==============================] - 8s 130us/step - loss: 0.0820 - acc: 0.9777
- val_loss: 0.0676 - val_acc: 0.9821
```

In [0]:

```
model3.summary()
```

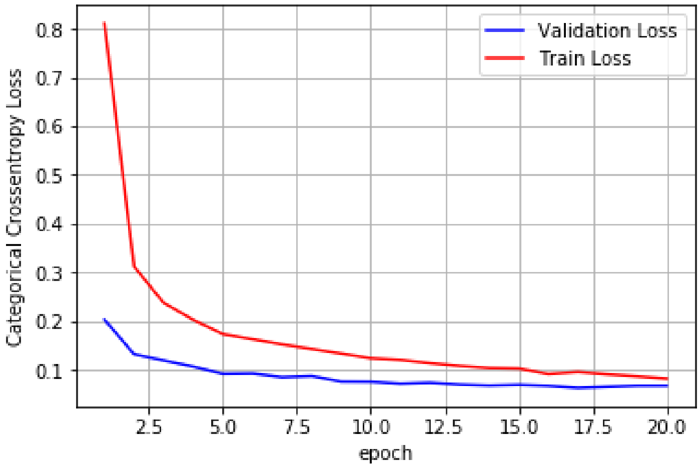
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_57 (Dense)             (None, 512)               401920
_________________________________________________________________
batch_normalization_19 (Batc (None, 512)               2048
_________________________________________________________________
dropout_18 (Dropout)         (None, 512)               0
_________________________________________________________________
dense_58 (Dense)             (None, 256)               131328
_________________________________________________________________
batch_normalization_20 (Batc (None, 256)               1024
_________________________________________________________________
dropout_19 (Dropout)         (None, 256)               0
_________________________________________________________________
dense_59 (Dense)             (None, 128)               32896
_________________________________________________________________
batch_normalization_21 (Batc (None, 128)               512
_________________________________________________________________
dropout_20 (Dropout)         (None, 128)               0
_________________________________________________________________
dense_60 (Dense)             (None, 64)                8256
_________________________________________________________________
batch_normalization_22 (Batc (None, 64)                256
_________________________________________________________________
dropout_21 (Dropout)         (None, 64)                0
_________________________________________________________________
dense_61 (Dense)             (None, 10)                650
=================================================================
Total params: 578,890
Trainable params: 576,970
Non-trainable params: 1,920
_________________________________________________________________
```

In [0]:

```
score = model3.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

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

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

# print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verb
ose=1, validation_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 epoc
hs

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

```
Test score: 0.06762448588523548
Test accuracy: 0.9821
```

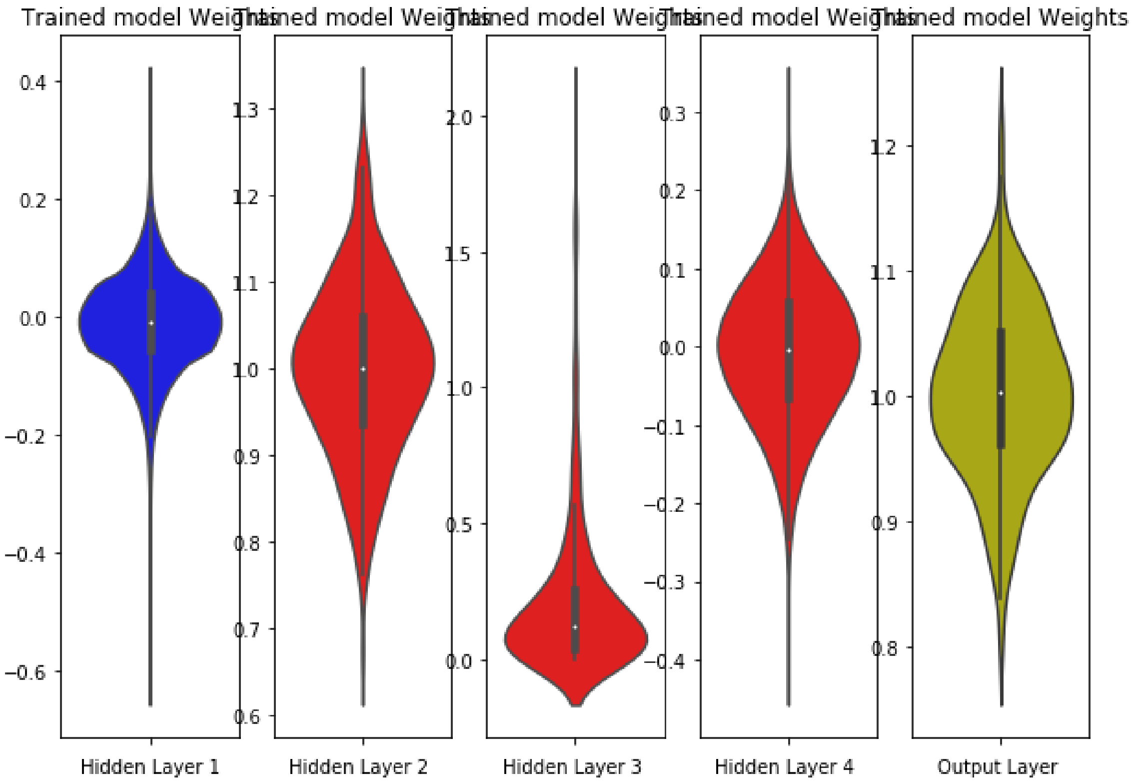


Better than many models.

In [0]:

```
w_after = model3.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)
out_w = w_after[8].flatten().reshape(-1,1)


fig = plt.figure(figsize=(10,7))
plt.title("Weight matrices after model trained")
plt.subplot(1, 5, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

plt.subplot(1, 5, 2)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden Layer 2 ')

plt.subplot(1, 5, 3)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h3_w, color='r')
plt.xlabel('Hidden Layer 3 ')

plt.subplot(1, 5, 4)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h4_w, color='r')
plt.xlabel('Hidden Layer 4 ')

plt.subplot(1, 5, 5)
plt.title("Trained model Weights")
```

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



4.1 RELU ACTIVATION WITH DROPOUT VALUE 0.5 (Optimiser - RMSPROP)

In [0]:

```
from keras.layers import Dropout
model4 = Sequential()
model4.add(Dense(512, input_dim=input_dim, activation='relu'))
model4.add(Dropout(0.5))
model4.add(Dense(256, input_dim=input_dim, activation='relu'))
model4.add(Dropout(0.5))
model4.add(Dense(128, input_dim=input_dim, activation='relu'))
model4.add(Dropout(0.5))
model4.add(Dense(10, input_dim=input_dim, activation='softmax'))
```

In [15]:

```
model4.compile(optimizer='RMSprop', loss='categorical_crossentropy', metrics=['accuracy'
])

history = model4.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1
, validation_data=(X_test, Y_test))
```

```
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/tensorflow/python/ops/math
_grad.py:1250: add_dispatch_support.<locals>.wrapper (from tensorflow.python.ops.array_op
s) is deprecated and will be removed in a future version.
Instructions for updating:
Use tf.where in 2.0, which has the same broadcast rule as np.where
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 8s 134us/step - loss: 0.5014 - acc: 0.8458
- val_loss: 0.1567 - val_acc: 0.9526
Epoch 2/20
60000/60000 [==============================] - 3s 54us/step - loss: 0.2250 - acc: 0.9398
- val_loss: 0.1244 - val_acc: 0.9663
Epoch 3/20
60000/60000 [==============================] - 3s 53us/step - loss: 0.1815 - acc: 0.9515
- val_loss: 0.1005 - val_acc: 0.9705
Epoch 4/20
60000/60000 [==============================] - 3s 54us/step - loss: 0.1602 - acc: 0.9590
- val_loss: 0.1014 - val_acc: 0.9744
Epoch 5/20
```

```
60000/60000 [==============================] - 3s 53us/step - loss: 0.1499 - acc: 0.9622
- val_loss: 0.0998 - val_acc: 0.9756
Epoch 6/20
60000/60000 [==============================] - 3s 53us/step - loss: 0.1418 - acc: 0.9658
- val_loss: 0.1051 - val_acc: 0.9761
Epoch 7/20
60000/60000 [==============================] - 3s 54us/step - loss: 0.1364 - acc: 0.9683
- val_loss: 0.1049 - val_acc: 0.9773
Epoch 8/20
60000/60000 [==============================] - 3s 53us/step - loss: 0.1353 - acc: 0.9694
- val_loss: 0.0956 - val_acc: 0.9786
Epoch 9/20
60000/60000 [==============================] - 3s 52us/step - loss: 0.1315 - acc: 0.9703
- val_loss: 0.1076 - val_acc: 0.9768
Epoch 10/20
60000/60000 [==============================] - 3s 53us/step - loss: 0.1315 - acc: 0.9708
- val_loss: 0.1046 - val_acc: 0.9795
Epoch 11/20
60000/60000 [==============================] - 3s 54us/step - loss: 0.1253 - acc: 0.9726
- val_loss: 0.1084 - val_acc: 0.9780
Epoch 12/20
60000/60000 [==============================] - 3s 54us/step - loss: 0.1214 - acc: 0.9734
- val_loss: 0.1086 - val_acc: 0.9803
Epoch 13/20
60000/60000 [==============================] - 3s 53us/step - loss: 0.1226 - acc: 0.9744
- val_loss: 0.1023 - val_acc: 0.9795
Epoch 14/20
60000/60000 [==============================] - 3s 54us/step - loss: 0.1199 - acc: 0.9748
- val_loss: 0.1110 - val_acc: 0.9791
Epoch 15/20
60000/60000 [==============================] - 3s 53us/step - loss: 0.1214 - acc: 0.9748
- val_loss: 0.1177 - val_acc: 0.9808
Epoch 16/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.1274 - acc: 0.9743
- val_loss: 0.1164 - val_acc: 0.9793
Epoch 17/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.1237 - acc: 0.9761
- val_loss: 0.1234 - val_acc: 0.9777
Epoch 18/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.1228 - acc: 0.9755
- val_loss: 0.1066 - val_acc: 0.9812
Epoch 19/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.1218 - acc: 0.9767
- val_loss: 0.1194 - val_acc: 0.9811
Epoch 20/20
60000/60000 [==============================] - 3s 55us/step - loss: 0.1302 - acc: 0.9756
- val_loss: 0.1145 - val_acc: 0.9794
```

In [16]:

```
model4.summary()
```

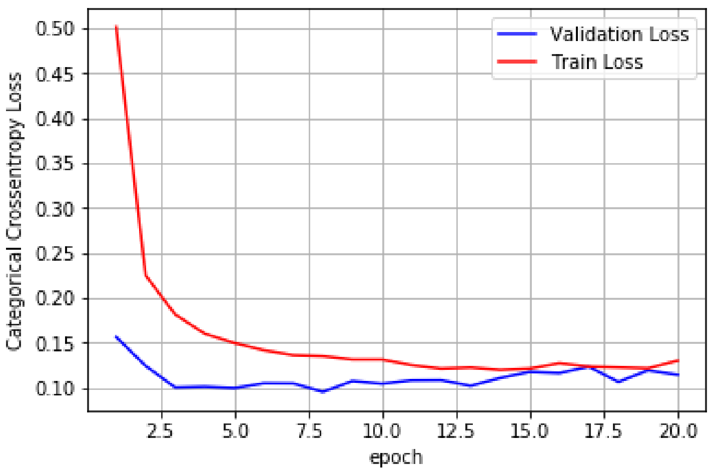
```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_5 (Dense)              (None, 512)               401920    
_________________________________________________________________
dropout_4 (Dropout)          (None, 512)               0         
_________________________________________________________________
dense_6 (Dense)              (None, 256)               131328    
_________________________________________________________________
dropout_5 (Dropout)          (None, 256)               0         
_________________________________________________________________
dense_7 (Dense)              (None, 128)               32896     
_________________________________________________________________
dropout_6 (Dropout)          (None, 128)               0         
_________________________________________________________________
dense_8 (Dense)              (None, 10)                1290      
=================================================================
Total params: 567,434
Trainable params: 567,434
```

```
Non-trainable params: 0
_________________________________________________________________
```

In [17]:

```
score = model4.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

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

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

# print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verb
ose=1, validation_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 epoc
hs

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

```
Test score: 0.11451425200372187
Test accuracy: 0.9794
```

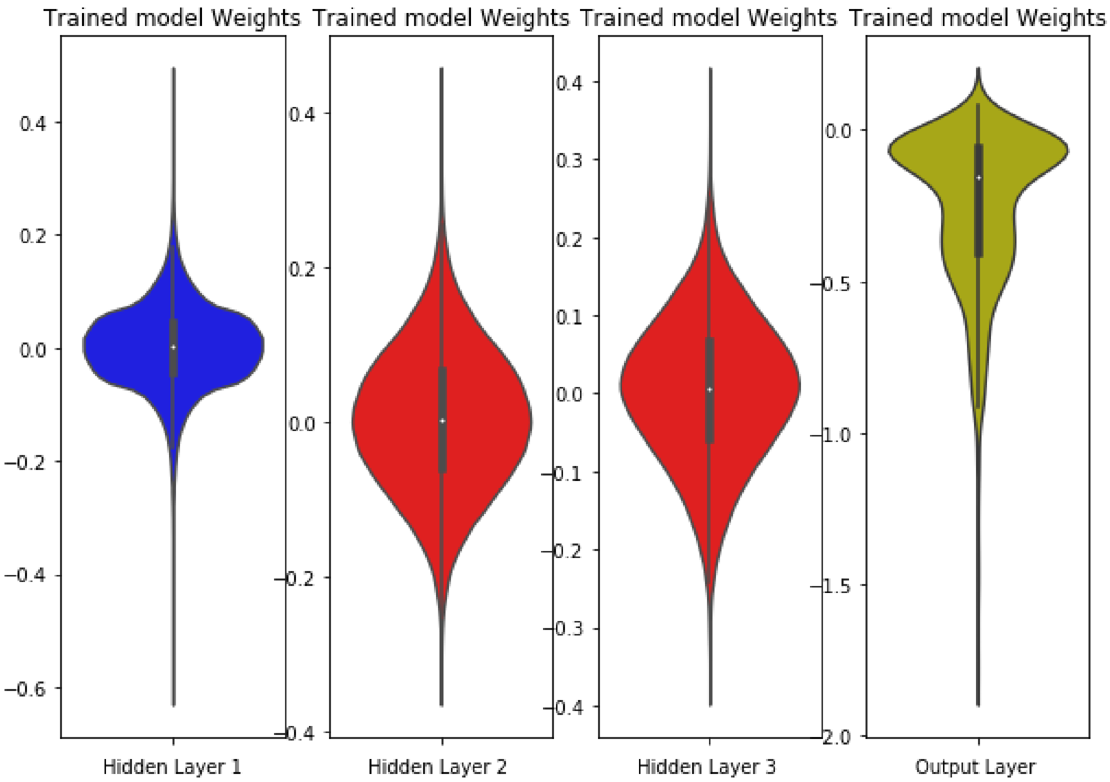


Good stats seen all along the epochs.

In [18]:

```
w_after = model4.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=(10,7))
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='r')
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()
```



4.2 RELU ACTIVATION WITH BATCH NORM AND DROPOUT(0.3) Optimiser-(RMSprop)

In [0]:

```
from keras.layers.normalization import BatchNormalization
model4 = Sequential()

model4.add(Dense(512, input_dim=input_dim, activation='relu'))
model4.add(BatchNormalization())
model4.add(Dropout(0.3))

model4.add(Dense(256, input_dim=input_dim, activation='relu'))
model4.add(BatchNormalization())
model4.add(Dropout(0.3))

model4.add(Dense(128, input_dim=input_dim, activation='relu'))
model4.add(BatchNormalization())
model4.add(Dropout(0.3))

model4.add(Dense(10, input_dim=input_dim, activation='softmax'))
```

In [20]:

```
model4.compile(optimizer='RMSprop', loss='categorical_crossentropy', metrics=['accuracy'
])

history = model4.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1
```

```
, validation_data=(X_test, Y_test))
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 7s 116us/step - loss: 0.2904 - acc: 0.9130
- val_loss: 0.1020 - val_acc: 0.9680
Epoch 2/20
60000/60000 [==============================] - 6s 103us/step - loss: 0.1353 - acc: 0.9599
- val_loss: 0.0881 - val_acc: 0.9724
Epoch 3/20
60000/60000 [==============================] - 6s 103us/step - loss: 0.1040 - acc: 0.9687
- val_loss: 0.0740 - val_acc: 0.9779
Epoch 4/20
60000/60000 [==============================] - 6s 102us/step - loss: 0.0854 - acc: 0.9735
- val_loss: 0.0634 - val_acc: 0.9809
Epoch 5/20
60000/60000 [==============================] - 6s 102us/step - loss: 0.0745 - acc: 0.9778
- val_loss: 0.0631 - val_acc: 0.9819
Epoch 6/20
60000/60000 [==============================] - 6s 101us/step - loss: 0.0641 - acc: 0.9803
- val_loss: 0.0611 - val_acc: 0.9814
Epoch 7/20
60000/60000 [==============================] - 6s 102us/step - loss: 0.0560 - acc: 0.9827
- val_loss: 0.0607 - val_acc: 0.9819
Epoch 8/20
60000/60000 [==============================] - 6s 102us/step - loss: 0.0522 - acc: 0.9847
- val_loss: 0.0626 - val_acc: 0.9831
Epoch 9/20
60000/60000 [==============================] - 6s 102us/step - loss: 0.0480 - acc: 0.9852
- val_loss: 0.0581 - val_acc: 0.9825
Epoch 10/20
60000/60000 [==============================] - 6s 103us/step - loss: 0.0440 - acc: 0.9863
- val_loss: 0.0636 - val_acc: 0.9818
Epoch 11/20
60000/60000 [==============================] - 6s 103us/step - loss: 0.0431 - acc: 0.9868
- val_loss: 0.0627 - val_acc: 0.9828
Epoch 12/20
60000/60000 [==============================] - 6s 101us/step - loss: 0.0366 - acc: 0.9889
- val_loss: 0.0626 - val_acc: 0.9822
Epoch 13/20
60000/60000 [==============================] - 6s 102us/step - loss: 0.0367 - acc: 0.9885
- val_loss: 0.0637 - val_acc: 0.9815
Epoch 14/20
60000/60000 [==============================] - 6s 105us/step - loss: 0.0376 - acc: 0.9884
- val_loss: 0.0573 - val_acc: 0.9852
Epoch 15/20
60000/60000 [==============================] - 6s 102us/step - loss: 0.0357 - acc: 0.9887
- val_loss: 0.0605 - val_acc: 0.9845
Epoch 16/20
60000/60000 [==============================] - 6s 100us/step - loss: 0.0314 - acc: 0.9896
- val_loss: 0.0632 - val_acc: 0.9836
Epoch 17/20
60000/60000 [==============================] - 6s 102us/step - loss: 0.0327 - acc: 0.9901
- val_loss: 0.0603 - val_acc: 0.9846
Epoch 18/20
60000/60000 [==============================] - 6s 101us/step - loss: 0.0290 - acc: 0.9908
- val_loss: 0.0581 - val_acc: 0.9838
Epoch 19/20
60000/60000 [==============================] - 6s 103us/step - loss: 0.0299 - acc: 0.9905
- val_loss: 0.0580 - val_acc: 0.9847
Epoch 20/20
60000/60000 [==============================] - 6s 103us/step - loss: 0.0264 - acc: 0.9917
- val_loss: 0.0585 - val_acc: 0.9854
```

In [21]:

```
model4.summary()
```

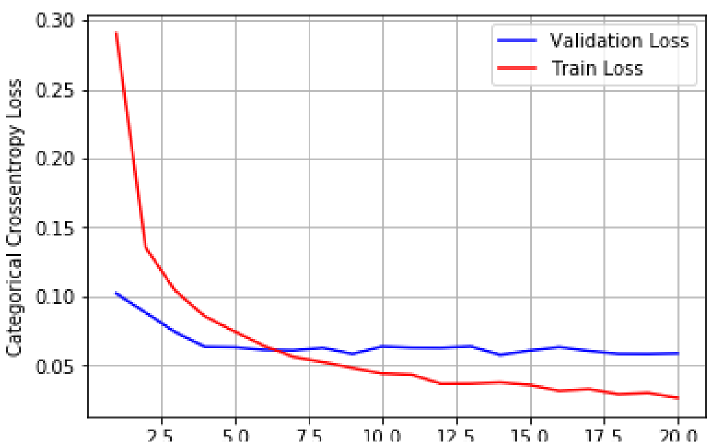
```
Model: "sequential_3"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
```

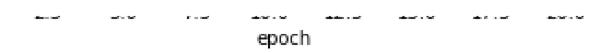
```
dense_9 (Dense)              (None, 512)               401920
_________________________________________________________________
batch_normalization_1 (Batch (None, 512)               2048
_________________________________________________________________
dropout_7 (Dropout)          (None, 512)               0
_________________________________________________________________
dense_10 (Dense)             (None, 256)               131328
_________________________________________________________________
batch_normalization_2 (Batch (None, 256)               1024
_________________________________________________________________
dropout_8 (Dropout)          (None, 256)               0
_________________________________________________________________
dense_11 (Dense)             (None, 128)               32896
_________________________________________________________________
batch_normalization_3 (Batch (None, 128)               512
_________________________________________________________________
dropout_9 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_12 (Dense)             (None, 10)                1290
=================================================================
Total params: 571,018
Trainable params: 569,226
Non-trainable params: 1,792
_________________________________________________________________
```

In [22]:

```
score = model4.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

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

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

# print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verb
ose=1, validation_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 epoc
hs

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

```
Test score: 0.05845784421725511
Test accuracy: 0.9854
```

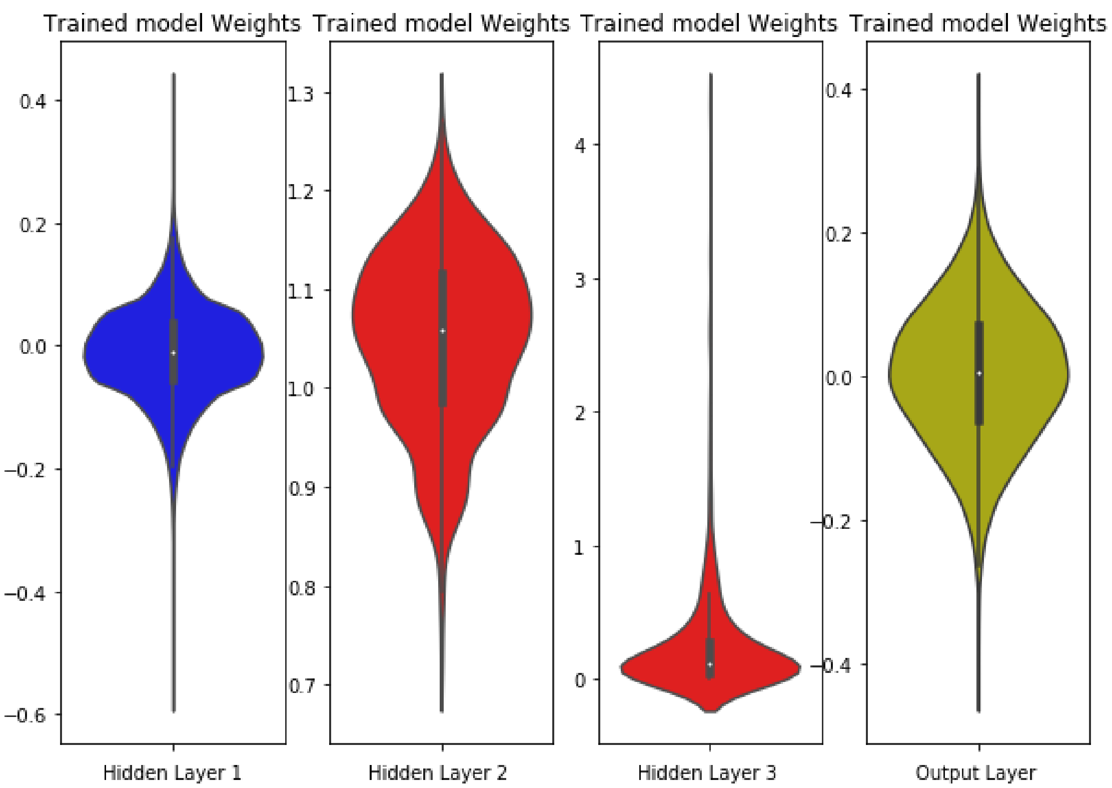




The little value of dropout made the model to overfit at 6th epoch.But the stats are good till the end.

In [23]:

```
w_after = model4.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=(10,7))
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='r')
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()
```



4.3 RELU ACTIVATION WITH BATCH NORM (Optimiser-RMSProp)

In [0]:

```
from keras.layers.normalization import BatchNormalization
model4 = Sequential()
```

```
model4.add(Dense(512, input_dim=input_dim, activation='relu'))
model4.add(BatchNormalization())

model4.add(Dense(256, input_dim=input_dim, activation='relu'))
model4.add(BatchNormalization())

model4.add(Dense(128, input_dim=input_dim, activation='relu'))
model4.add(BatchNormalization())

model4.add(Dense(10, input_dim=input_dim, activation='softmax'))
```

In [25]:

```
model4.compile(optimizer='RMSprop', loss='categorical_crossentropy', metrics=['accuracy'
])

history = model4.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1
, validation_data=(X_test, Y_test))
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 7s 111us/step - loss: 0.1710 - acc: 0.9479
- val_loss: 0.0983 - val_acc: 0.9690
Epoch 2/20
60000/60000 [==============================] - 6s 95us/step - loss: 0.0748 - acc: 0.9770
- val_loss: 0.0898 - val_acc: 0.9725
Epoch 3/20
60000/60000 [==============================] - 6s 95us/step - loss: 0.0495 - acc: 0.9848
- val_loss: 0.0716 - val_acc: 0.9778
Epoch 4/20
60000/60000 [==============================] - 6s 95us/step - loss: 0.0369 - acc: 0.9885
- val_loss: 0.0698 - val_acc: 0.9793
Epoch 5/20
60000/60000 [==============================] - 6s 94us/step - loss: 0.0270 - acc: 0.9913
- val_loss: 0.0714 - val_acc: 0.9787
Epoch 6/20
60000/60000 [==============================] - 6s 94us/step - loss: 0.0239 - acc: 0.9924
- val_loss: 0.0660 - val_acc: 0.9816
Epoch 7/20
60000/60000 [==============================] - 6s 96us/step - loss: 0.0178 - acc: 0.9944
- val_loss: 0.0843 - val_acc: 0.9796
Epoch 8/20
60000/60000 [==============================] - 6s 96us/step - loss: 0.0167 - acc: 0.9941
- val_loss: 0.0697 - val_acc: 0.9812
Epoch 9/20
60000/60000 [==============================] - 6s 96us/step - loss: 0.0134 - acc: 0.9957
- val_loss: 0.0827 - val_acc: 0.9799
Epoch 10/20
60000/60000 [==============================] - 6s 95us/step - loss: 0.0121 - acc: 0.9961
- val_loss: 0.0769 - val_acc: 0.9828
Epoch 11/20
60000/60000 [==============================] - 6s 97us/step - loss: 0.0114 - acc: 0.9961
- val_loss: 0.0700 - val_acc: 0.9828
Epoch 12/20
60000/60000 [==============================] - 6s 95us/step - loss: 0.0104 - acc: 0.9965
- val_loss: 0.0743 - val_acc: 0.9828
Epoch 13/20
60000/60000 [==============================] - 6s 98us/step - loss: 0.0096 - acc: 0.9970
- val_loss: 0.0836 - val_acc: 0.9821
Epoch 14/20
60000/60000 [==============================] - 6s 96us/step - loss: 0.0080 - acc: 0.9975
- val_loss: 0.0875 - val_acc: 0.9807
Epoch 15/20
60000/60000 [==============================] - 6s 97us/step - loss: 0.0065 - acc: 0.9978
- val_loss: 0.0875 - val_acc: 0.9803
Epoch 16/20
60000/60000 [==============================] - 6s 95us/step - loss: 0.0078 - acc: 0.9974
- val_loss: 0.0900 - val_acc: 0.9823
Epoch 17/20
60000/60000 [==============================] - 6s 96us/step - loss: 0.0065 - acc: 0.9978
- val_loss: 0.0847 - val_acc: 0.9820
```

```
Epoch 18/20
60000/60000 [==============================] - 6s 94us/step - loss: 0.0078 - acc: 0.9973
- val_loss: 0.0875 - val_acc: 0.9822
Epoch 19/20
60000/60000 [==============================] - 6s 96us/step - loss: 0.0064 - acc: 0.9979
- val_loss: 0.0917 - val_acc: 0.9808
Epoch 20/20
60000/60000 [==============================] - 6s 94us/step - loss: 0.0068 - acc: 0.9979
- val_loss: 0.1034 - val_acc: 0.9799
```

In [26]:

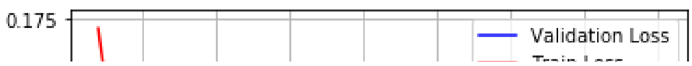
```
model4.summary()
```

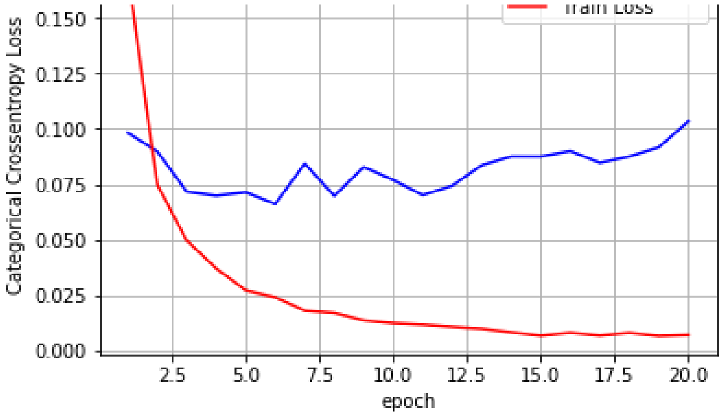
```
Model: "sequential_4"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_13 (Dense)             (None, 512)               401920
_________________________________________________________________
batch_normalization_4 (Batch (None, 512)               2048
_________________________________________________________________
dense_14 (Dense)             (None, 256)               131328
_________________________________________________________________
batch_normalization_5 (Batch (None, 256)               1024
_________________________________________________________________
dense_15 (Dense)             (None, 128)               32896
_________________________________________________________________
batch_normalization_6 (Batch (None, 128)               512
_________________________________________________________________
dense_16 (Dense)             (None, 10)                1290
=================================================================
Total params: 571,018
Trainable params: 569,226
Non-trainable params: 1,792
_________________________________________________________________
```

In [27]:

```
score = model4.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

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

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

# print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verb
ose=1, validation_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 epoc
hs

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

```
Test score: 0.10336758222593094
Test accuracy: 0.9799
```

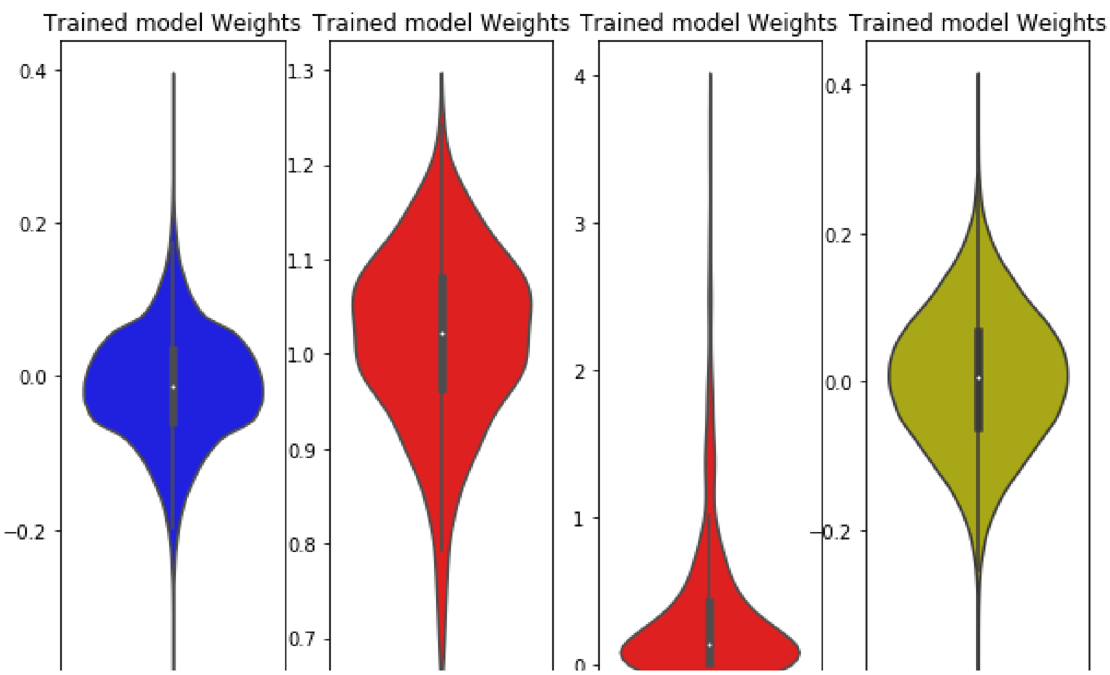


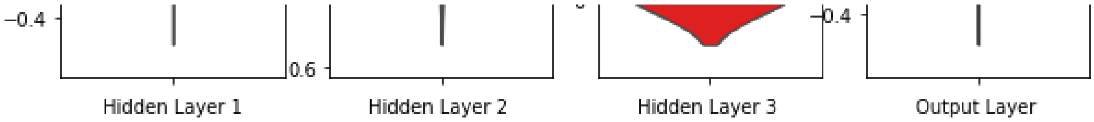


Best case of overfitting till now.

In [28]:

```
w_after = model4.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=(10,7))
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='r')
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()
```





5.1 SIGMOID ACTIVATION WITH DROPOUT VALUE 0.4 (Optimiser - SGD)

In [0]:

```
from keras.layers import Dropout
model5 = Sequential()
model5.add(Dense(512, input_dim=input_dim, activation='relu'))
model5.add(Dropout(0.4))
model5.add(Dense(256, input_dim=input_dim, activation='relu'))
model5.add(Dropout(0.4))
model5.add(Dense(128, input_dim=input_dim, activation='relu'))
model5.add(Dropout(0.4))
model5.add(Dense(10, input_dim=input_dim, activation='softmax'))
```

In [32]:

```
model5.compile(optimizer='SGD', loss='categorical_crossentropy', metrics=['accuracy'])

history = model5.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 [==============================] - 4s 60us/step - loss: 1.6945 - acc: 0.4247
- val_loss: 0.7545 - val_acc: 0.8054
Epoch 2/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.8934 - acc: 0.7086
- val_loss: 0.4545 - val_acc: 0.8809
Epoch 3/20
60000/60000 [==============================] - 3s 51us/step - loss: 0.6628 - acc: 0.7939
- val_loss: 0.3635 - val_acc: 0.8979
Epoch 4/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.5537 - acc: 0.8311
- val_loss: 0.3132 - val_acc: 0.9098
Epoch 5/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.4898 - acc: 0.8530
- val_loss: 0.2830 - val_acc: 0.9185
Epoch 6/20
60000/60000 [==============================] - 3s 51us/step - loss: 0.4421 - acc: 0.8677
- val_loss: 0.2596 - val_acc: 0.9258
Epoch 7/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.4044 - acc: 0.8799
- val_loss: 0.2398 - val_acc: 0.9323
Epoch 8/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.3773 - acc: 0.8892
- val_loss: 0.2242 - val_acc: 0.9358
Epoch 9/20
60000/60000 [==============================] - 3s 48us/step - loss: 0.3526 - acc: 0.8969
- val_loss: 0.2114 - val_acc: 0.9388
Epoch 10/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.3277 - acc: 0.9035
- val_loss: 0.2009 - val_acc: 0.9419
Epoch 11/20
60000/60000 [==============================] - 3s 49us/step - loss: 0.3163 - acc: 0.9077
- val_loss: 0.1889 - val_acc: 0.9438
Epoch 12/20
60000/60000 [==============================] - 3s 49us/step - loss: 0.2980 - acc: 0.9135
- val_loss: 0.1803 - val_acc: 0.9468
Epoch 13/20
60000/60000 [==============================] - 3s 49us/step - loss: 0.2865 - acc: 0.9159
- val_loss: 0.1740 - val_acc: 0.9486
Epoch 14/20
60000/60000 [==============================] - 3s 49us/step - loss: 0.2725 - acc: 0.9204
- val_loss: 0.1666 - val_acc: 0.9505
Epoch 15/20
60000/60000 [==============================] - 3s 47us/step - loss: 0.2644 - acc: 0.9234
```

```
- val_loss: 0.1596 - val_acc: 0.9514
Epoch 16/20
60000/60000 [==============================] - 3s 48us/step - loss: 0.2512 - acc: 0.9270
- val_loss: 0.1553 - val_acc: 0.9532
Epoch 17/20
60000/60000 [==============================] - 3s 49us/step - loss: 0.2406 - acc: 0.9304
- val_loss: 0.1481 - val_acc: 0.9554
Epoch 18/20
60000/60000 [==============================] - 3s 49us/step - loss: 0.2339 - acc: 0.9313
- val_loss: 0.1443 - val_acc: 0.9553
Epoch 19/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.2260 - acc: 0.9342
- val_loss: 0.1392 - val_acc: 0.9568
Epoch 20/20
60000/60000 [==============================] - 3s 50us/step - loss: 0.2186 - acc: 0.9363
- val_loss: 0.1357 - val_acc: 0.9590
```

In [33]:

```
model5.summary()
```

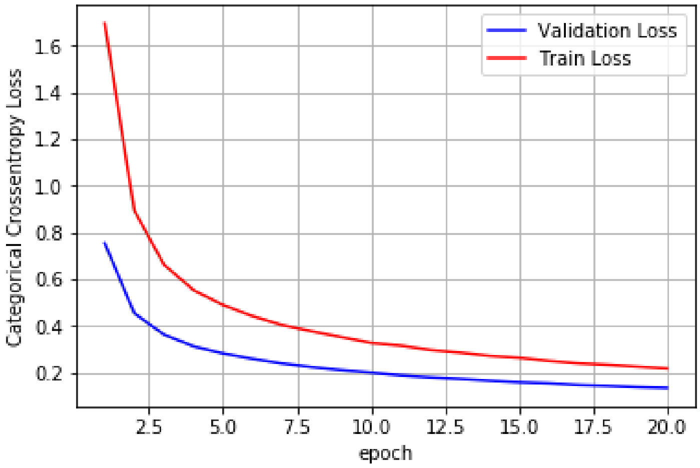
```
Model: "sequential_6"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_21 (Dense)             (None, 512)               401920    
_________________________________________________________________
dropout_13 (Dropout)         (None, 512)               0         
_________________________________________________________________
dense_22 (Dense)             (None, 256)               131328    
_________________________________________________________________
dropout_14 (Dropout)         (None, 256)               0         
_________________________________________________________________
dense_23 (Dense)             (None, 128)               32896     
_________________________________________________________________
dropout_15 (Dropout)         (None, 128)               0         
_________________________________________________________________
dense_24 (Dense)             (None, 10)                1290      
=================================================================
Total params: 567,434
Trainable params: 567,434
Non-trainable params: 0
_________________________________________________________________
```

In [34]:

```
score = model5.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

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

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

# print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verb
ose=1, validation_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 epoc
hs

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

```
plt_dynamic(x, vy, ty, ax)
```

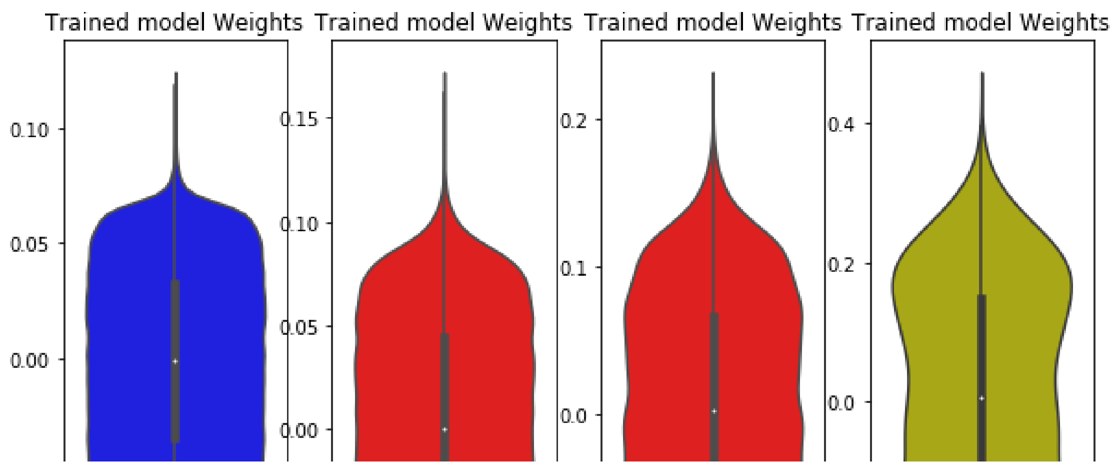
```
Test score: 0.13570419172216205
Test accuracy: 0.959
```

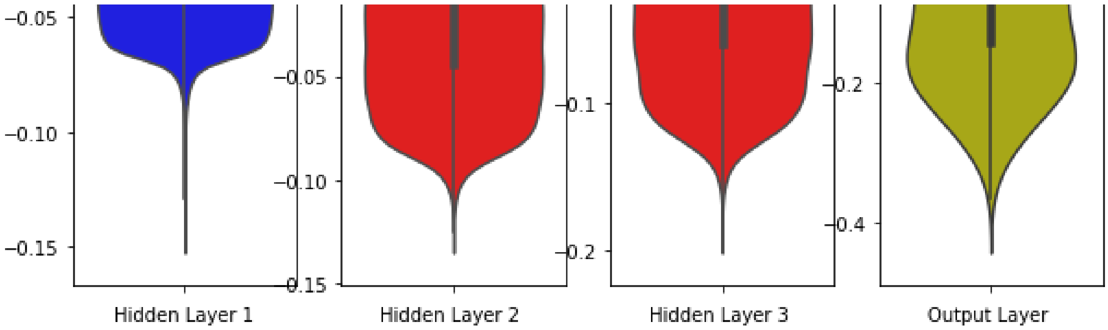


Although it is a slow learner there is no under fitting nor overfitting.

In [35]:

```
w_after = model5.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=(10,7))
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='r')
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()
```





5.2 RELU ACTIVATION WITH BATCH NORM AND DROPOUT(0.3) Optimiser-(SGD)

In [0]:

```
from keras.layers.normalization import BatchNormalization
model5 = Sequential()

model5.add(Dense(512, input_dim=input_dim, activation='relu'))
model5.add(BatchNormalization())
model5.add(Dropout(0.3))

model5.add(Dense(256, input_dim=input_dim, activation='relu'))
model5.add(BatchNormalization())
model5.add(Dropout(0.3))

model5.add(Dense(128, input_dim=input_dim, activation='relu'))
model5.add(BatchNormalization())
model5.add(Dropout(0.3))

model5.add(Dense(10, input_dim=input_dim, activation='softmax'))
```

In [37]:

```
model5.compile(optimizer='SGD', loss='categorical_crossentropy', metrics=['accuracy'])

history = model5.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1
, validation_data=(X_test, Y_test))
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 7s 110us/step - loss: 0.7637 - acc: 0.7637
- val_loss: 0.2561 - val_acc: 0.9228
Epoch 2/20
60000/60000 [==============================] - 5s 88us/step - loss: 0.3820 - acc: 0.8831
- val_loss: 0.1963 - val_acc: 0.9411
Epoch 3/20
60000/60000 [==============================] - 5s 87us/step - loss: 0.3091 - acc: 0.9053
- val_loss: 0.1665 - val_acc: 0.9495
Epoch 4/20
60000/60000 [==============================] - 5s 88us/step - loss: 0.2655 - acc: 0.9186
- val_loss: 0.1480 - val_acc: 0.9553
Epoch 5/20
60000/60000 [==============================] - 5s 88us/step - loss: 0.2400 - acc: 0.9280
- val_loss: 0.1334 - val_acc: 0.9599
Epoch 6/20
60000/60000 [==============================] - 5s 89us/step - loss: 0.2181 - acc: 0.9343
- val_loss: 0.1250 - val_acc: 0.9617
Epoch 7/20
60000/60000 [==============================] - 5s 89us/step - loss: 0.2011 - acc: 0.9397
- val_loss: 0.1174 - val_acc: 0.9644
Epoch 8/20
60000/60000 [==============================] - 5s 88us/step - loss: 0.1863 - acc: 0.9437
- val_loss: 0.1116 - val_acc: 0.9671
Epoch 9/20
60000/60000 [==============================] - 5s 89us/step - loss: 0.1742 - acc: 0.9469
- val_loss: 0.1057 - val_acc: 0.9675
Epoch 10/20
60000/60000 [==============================] - 6s 92us/step - loss: 0.1681 - acc: 0.9495
- val_loss: 0.1010 - val_acc: 0.9689
```

```
Epoch 11/20
60000/60000 [==============================] - 5s 88us/step - loss: 0.1544 - acc: 0.9541
- val_loss: 0.0969 - val_acc: 0.9701
Epoch 12/20
60000/60000 [==============================] - 5s 87us/step - loss: 0.1475 - acc: 0.9554
- val_loss: 0.0932 - val_acc: 0.9719
Epoch 13/20
60000/60000 [==============================] - 5s 88us/step - loss: 0.1393 - acc: 0.9568
- val_loss: 0.0904 - val_acc: 0.9723
Epoch 14/20
60000/60000 [==============================] - 5s 91us/step - loss: 0.1368 - acc: 0.9580
- val_loss: 0.0862 - val_acc: 0.9739
Epoch 15/20
60000/60000 [==============================] - 5s 89us/step - loss: 0.1292 - acc: 0.9606
- val_loss: 0.0838 - val_acc: 0.9739
Epoch 16/20
60000/60000 [==============================] - 5s 89us/step - loss: 0.1238 - acc: 0.9619
- val_loss: 0.0824 - val_acc: 0.9747
Epoch 17/20
60000/60000 [==============================] - 5s 89us/step - loss: 0.1200 - acc: 0.9626
- val_loss: 0.0809 - val_acc: 0.9753
Epoch 18/20
60000/60000 [==============================] - 5s 91us/step - loss: 0.1132 - acc: 0.9653
- val_loss: 0.0780 - val_acc: 0.9755
Epoch 19/20
60000/60000 [==============================] - 6s 95us/step - loss: 0.1096 - acc: 0.9660
- val_loss: 0.0770 - val_acc: 0.9766
Epoch 20/20
60000/60000 [==============================] - 6s 92us/step - loss: 0.1047 - acc: 0.9675
- val_loss: 0.0760 - val_acc: 0.9763
```

In [38]:

```
model5.summary()
```

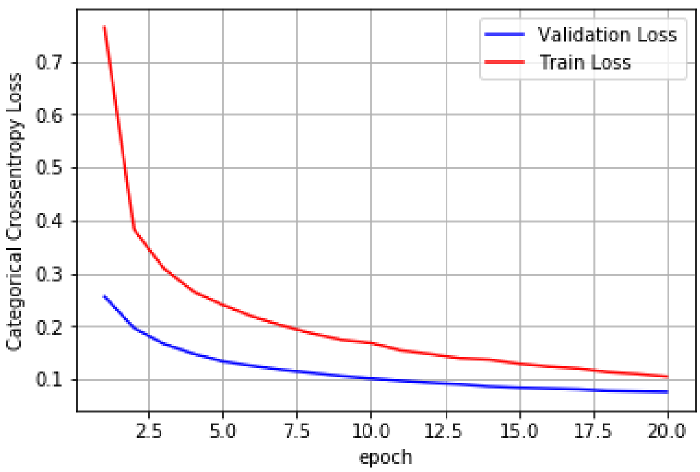
```
Model: "sequential_7"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_25 (Dense)             (None, 512)               401920    
_________________________________________________________________
batch_normalization_7 (Batch (None, 512)               2048      
_________________________________________________________________
dropout_16 (Dropout)         (None, 512)               0         
_________________________________________________________________
dense_26 (Dense)             (None, 256)               131328    
_________________________________________________________________
batch_normalization_8 (Batch (None, 256)               1024      
_________________________________________________________________
dropout_17 (Dropout)         (None, 256)               0         
_________________________________________________________________
dense_27 (Dense)             (None, 128)               32896     
_________________________________________________________________
batch_normalization_9 (Batch (None, 128)               512       
_________________________________________________________________
dropout_18 (Dropout)         (None, 128)               0         
_________________________________________________________________
dense_28 (Dense)             (None, 10)                1290      
=================================================================
Total params: 571,018
Trainable params: 569,226
Non-trainable params: 1,792
_________________________________________________________________
```

In [39]:

```
score = model5.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

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

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

# print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verb
ose=1, validation_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 epoc
hs

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

```
Test score: 0.07599864422457758
Test accuracy: 0.9763
```

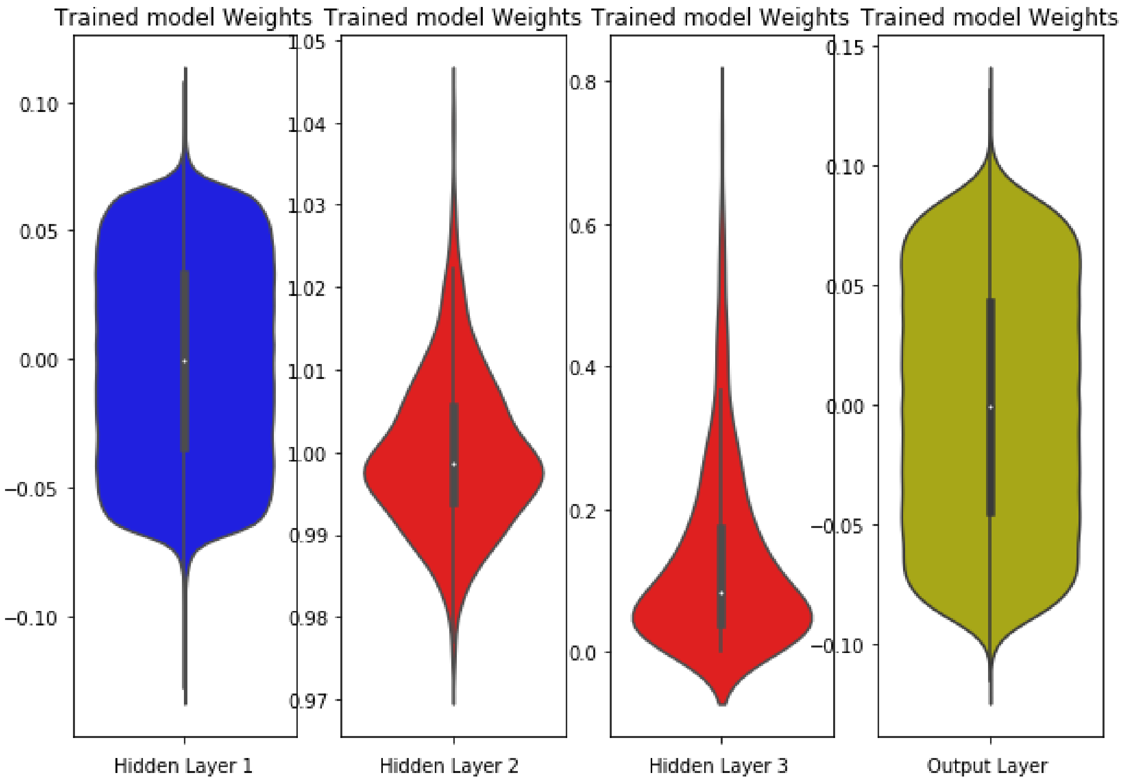


The little value of dropout made the model to learn faster than the previous model and all the stats are good till the end.

In [40]:

```
w_after = model5.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=(10,7))
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='r')
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()
```



5.3 RELU ACTIVATION WITH BATCH NORM (Optimiser-SGD)

In [0]:

```
from keras.layers.normalization import BatchNormalization
model5 = Sequential()

model5.add(Dense(512, input_dim=input_dim, activation='relu'))
model5.add(BatchNormalization())

model5.add(Dense(256, input_dim=input_dim, activation='relu'))
model5.add(BatchNormalization())

model5.add(Dense(128, input_dim=input_dim, activation='relu'))
model5.add(BatchNormalization())

model5.add(Dense(10, input_dim=input_dim, activation='softmax'))
```

In [42]:

```
model5.compile(optimizer='SGD', loss='categorical_crossentropy', metrics=['accuracy'])

history = model5.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 [==============================] - 6s 108us/step - loss: 0.4255 - acc: 0.8754
- val_loss: 0.2161 - val_acc: 0.9380
Epoch 2/20
60000/60000 [==============================] - 5s 84us/step - loss: 0.1857 - acc: 0.9478
- val_loss: 0.1634 - val_acc: 0.9521
Epoch 3/20
60000/60000 [==============================] - 5s 86us/step - loss: 0.1367 - acc: 0.9627
- val_loss: 0.1384 - val_acc: 0.9593
Epoch 4/20
60000/60000 [==============================] - 5s 86us/step - loss: 0.1096 - acc: 0.9708
- val_loss: 0.1243 - val_acc: 0.9636
```

```
Epoch 5/20
60000/60000 [==============================] - 5s 89us/step - loss: 0.0915 - acc: 0.9758
- val_loss: 0.1153 - val_acc: 0.9649
Epoch 6/20
60000/60000 [==============================] - 5s 88us/step - loss: 0.0771 - acc: 0.9805
- val_loss: 0.1084 - val_acc: 0.9663
Epoch 7/20
60000/60000 [==============================] - 5s 87us/step - loss: 0.0652 - acc: 0.9842
- val_loss: 0.1027 - val_acc: 0.9681
Epoch 8/20
60000/60000 [==============================] - 5s 87us/step - loss: 0.0573 - acc: 0.9860
- val_loss: 0.0985 - val_acc: 0.9687
Epoch 9/20
60000/60000 [==============================] - 5s 83us/step - loss: 0.0493 - acc: 0.9886
- val_loss: 0.0954 - val_acc: 0.9698
Epoch 10/20
60000/60000 [==============================] - 5s 87us/step - loss: 0.0429 - acc: 0.9906
- val_loss: 0.0923 - val_acc: 0.9705
Epoch 11/20
60000/60000 [==============================] - 5s 87us/step - loss: 0.0380 - acc: 0.9919
- val_loss: 0.0906 - val_acc: 0.9713
Epoch 12/20
60000/60000 [==============================] - 5s 88us/step - loss: 0.0333 - acc: 0.9932
- val_loss: 0.0893 - val_acc: 0.9715
Epoch 13/20
60000/60000 [==============================] - 5s 89us/step - loss: 0.0297 - acc: 0.9945
- val_loss: 0.0873 - val_acc: 0.9723
Epoch 14/20
60000/60000 [==============================] - 5s 90us/step - loss: 0.0261 - acc: 0.9956
- val_loss: 0.0865 - val_acc: 0.9725
Epoch 15/20
60000/60000 [==============================] - 5s 87us/step - loss: 0.0236 - acc: 0.9961
- val_loss: 0.0846 - val_acc: 0.9714
Epoch 16/20
60000/60000 [==============================] - 5s 87us/step - loss: 0.0213 - acc: 0.9974
- val_loss: 0.0844 - val_acc: 0.9723
Epoch 17/20
60000/60000 [==============================] - 5s 85us/step - loss: 0.0195 - acc: 0.9975
- val_loss: 0.0841 - val_acc: 0.9723
Epoch 18/20
60000/60000 [==============================] - 5s 86us/step - loss: 0.0177 - acc: 0.9979
- val_loss: 0.0829 - val_acc: 0.9726
Epoch 19/20
60000/60000 [==============================] - 5s 86us/step - loss: 0.0163 - acc: 0.9983
- val_loss: 0.0830 - val_acc: 0.9735
Epoch 20/20
60000/60000 [==============================] - 5s 86us/step - loss: 0.0147 - acc: 0.9986
- val_loss: 0.0824 - val_acc: 0.9741
```

In [43]:

```
model5.summary()
```

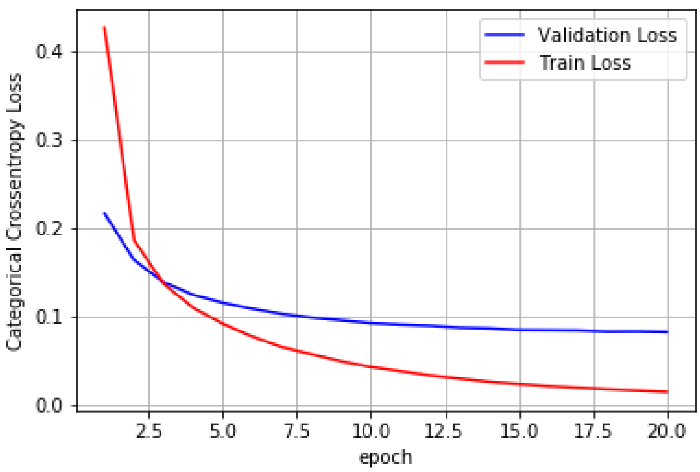
```
Model: "sequential_8"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_29 (Dense)             (None, 512)               401920    
_________________________________________________________________
batch_normalization_10 (Batc (None, 512)               2048      
_________________________________________________________________
dense_30 (Dense)             (None, 256)               131328    
_________________________________________________________________
batch_normalization_11 (Batc (None, 256)               1024      
_________________________________________________________________
dense_31 (Dense)             (None, 128)               32896     
_________________________________________________________________
batch_normalization_12 (Batc (None, 128)               512       
_________________________________________________________________
dense_32 (Dense)             (None, 10)                1290      
=================================================================
Total params: 571,018
```

```
Trainable params: 569,226
Non-trainable params: 1,792
_________________________________________________________________
```

In [44]:

```
score = model5.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

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

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

# print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verb
ose=1, validation_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 epoc
hs

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

```
Test score: 0.08236163575346582
Test accuracy: 0.9741
```

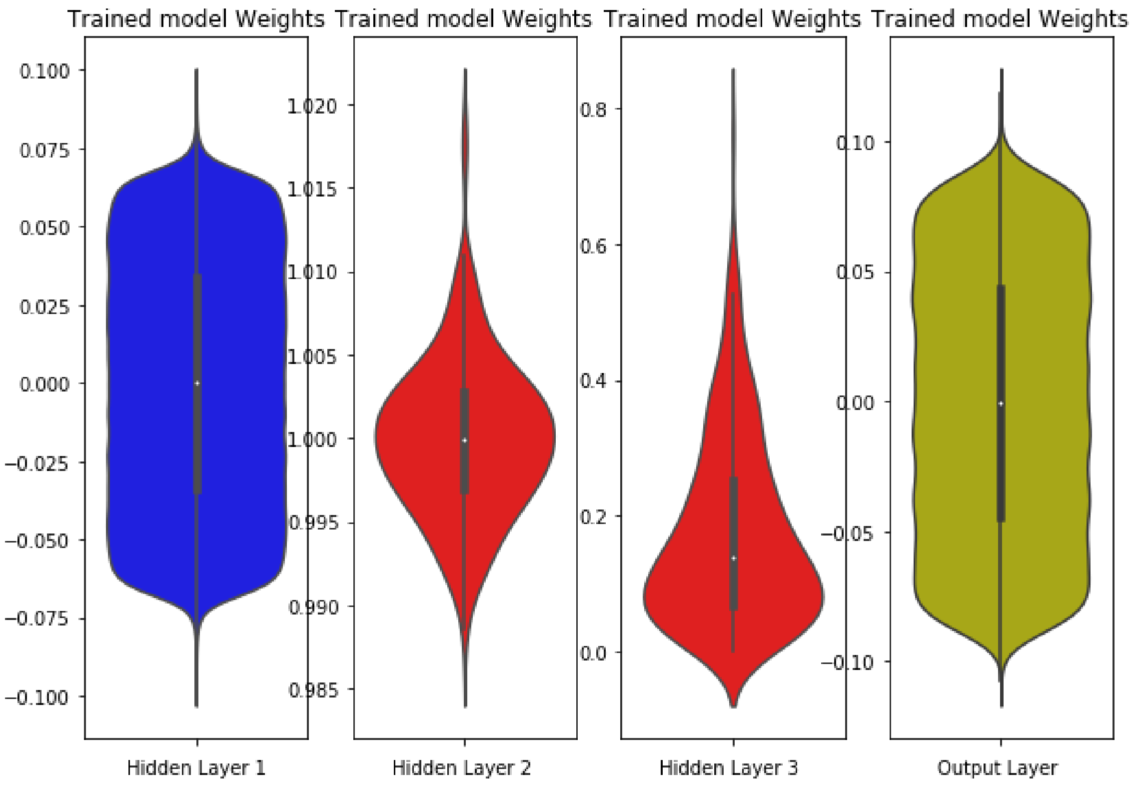


The validation loss is little slow in decreasing.

In [45]:

```
w_after = model5.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=(10,7))
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='r')
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()
```



6.1 RELU ACTIVATION WITH DROPOUT VALUE 0.5 (Optimiser - Adamax)

In [0]:

```
from keras.layers import Dropout
model5 = Sequential()
model5.add(Dense(512, input_dim=input_dim, activation='relu'))
model5.add(Dropout(0.5))
model5.add(Dense(256, input_dim=input_dim, activation='relu'))
model5.add(Dropout(0.5))
model5.add(Dense(128, input_dim=input_dim, activation='relu'))
model5.add(Dropout(0.5))
model5.add(Dense(10, input_dim=input_dim, activation='softmax'))
```

In [47]:

```
model5.compile(optimizer='Adamax', loss='categorical_crossentropy', metrics=['accuracy']
)

history = model5.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 [==============================] - 4s 74us/step - loss: 0.6029 - acc: 0.8106
- val_loss: 0.1855 - val_acc: 0.9462
Epoch 2/20
```

```
Epoch 2/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.2661 - acc: 0.9249
- val_loss: 0.1303 - val_acc: 0.9616
Epoch 3/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.2040 - acc: 0.9435
- val_loss: 0.1082 - val_acc: 0.9684
Epoch 4/20
60000/60000 [==============================] - 3s 58us/step - loss: 0.1697 - acc: 0.9525
- val_loss: 0.1010 - val_acc: 0.9697
Epoch 5/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.1498 - acc: 0.9588
- val_loss: 0.0895 - val_acc: 0.9731
Epoch 6/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.1317 - acc: 0.9628
- val_loss: 0.0844 - val_acc: 0.9750
Epoch 7/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.1191 - acc: 0.9661
- val_loss: 0.0801 - val_acc: 0.9757
Epoch 8/20
60000/60000 [==============================] - 4s 58us/step - loss: 0.1090 - acc: 0.9690
- val_loss: 0.0767 - val_acc: 0.9775
Epoch 9/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.1007 - acc: 0.9721
- val_loss: 0.0751 - val_acc: 0.9790
Epoch 10/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.0942 - acc: 0.9738
- val_loss: 0.0755 - val_acc: 0.9792
Epoch 11/20
60000/60000 [==============================] - 3s 58us/step - loss: 0.0877 - acc: 0.9749
- val_loss: 0.0742 - val_acc: 0.9793
Epoch 12/20
60000/60000 [==============================] - 4s 59us/step - loss: 0.0818 - acc: 0.9773
- val_loss: 0.0689 - val_acc: 0.9814
Epoch 13/20
60000/60000 [==============================] - 4s 59us/step - loss: 0.0779 - acc: 0.9777
- val_loss: 0.0698 - val_acc: 0.9809
Epoch 14/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.0733 - acc: 0.9784
- val_loss: 0.0678 - val_acc: 0.9814
Epoch 15/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.0709 - acc: 0.9797
- val_loss: 0.0687 - val_acc: 0.9816
Epoch 16/20
60000/60000 [==============================] - 3s 56us/step - loss: 0.0670 - acc: 0.9805
- val_loss: 0.0688 - val_acc: 0.9813
Epoch 17/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.0648 - acc: 0.9810
- val_loss: 0.0694 - val_acc: 0.9808
Epoch 18/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.0612 - acc: 0.9817
- val_loss: 0.0661 - val_acc: 0.9830
Epoch 19/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.0582 - acc: 0.9824
- val_loss: 0.0668 - val_acc: 0.9823
Epoch 20/20
60000/60000 [==============================] - 3s 57us/step - loss: 0.0561 - acc: 0.9841
- val_loss: 0.0660 - val_acc: 0.9832
```

In [48]:

```
model5.summary()
```

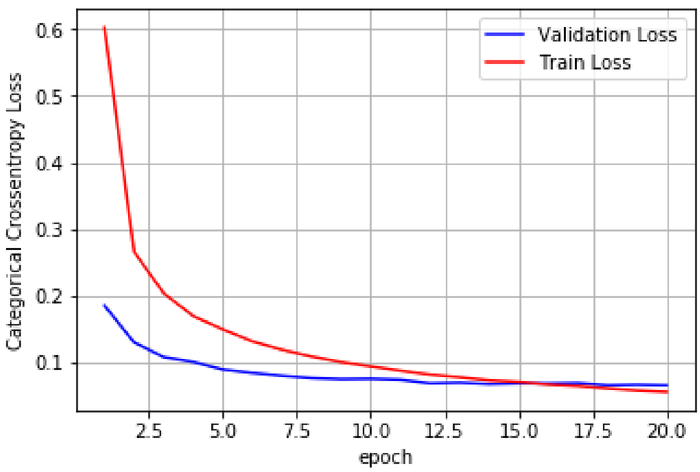
```
Model: "sequential_9"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_33 (Dense)             (None, 512)               401920
_________________________________________________________________
dropout_19 (Dropout)         (None, 512)               0
_________________________________________________________________
dense_34 (Dense)             (None, 256)               131328
_________________________________________________________________
dropout_20 (Dropout)         (None, 256)               0
```

```
dropout_20 (Dropout)         (None, 256)               0
_________________________________________________________________
dense_35 (Dense)             (None, 128)               32896
_________________________________________________________________
dropout_21 (Dropout)         (None, 128)               0
_________________________________________________________________
dense_36 (Dense)             (None, 10)                1290
=================================================================
Total params: 567,434
Trainable params: 567,434
Non-trainable params: 0
_________________________________________________________________
```

In [49]:

```
score = model5.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

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

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

# print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verb
ose=1, validation_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 epoc
hs

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

```
Test score: 0.06598338727326336
Test accuracy: 0.9832
```

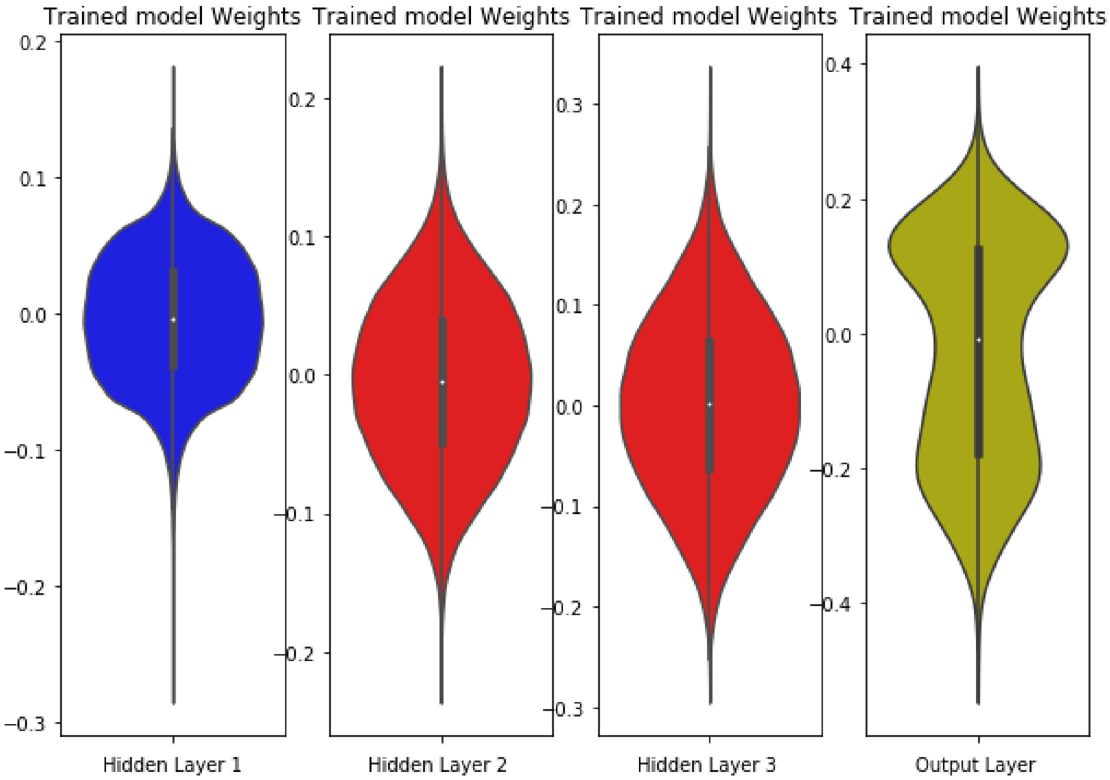


Good stats seen all along the epochs.Overfitting at 15th epoch.

In [50]:

```
w_after = model5.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=(10,7))
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='r')
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()
```



6.2 RELU ACTIVATION WITH BATCH NORM AND DROPOUT(0.3) Optimiser-(Adamax)

In [0]:

```
from keras.layers.normalization import BatchNormalization
model6 = Sequential()

model6.add(Dense(512, input_dim=input_dim, activation='relu'))
model6.add(BatchNormalization())
model6.add(Dropout(0.3))

model6.add(Dense(256, input_dim=input_dim, activation='relu'))
model6.add(BatchNormalization())
model6.add(Dropout(0.3))

model6.add(Dense(128, input_dim=input_dim, activation='relu'))
model6.add(BatchNormalization())
model6.add(Dropout(0.3))
```

```
model6.add(Dense(10, input_dim=input_dim, activation='softmax'))
```

In [52]:

```
model6.compile(optimizer='Adamax', loss='categorical_crossentropy', metrics=['accuracy']
)

history = model6.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1
, validation_data=(X_test, Y_test))
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 8s 130us/step - loss: 0.3441 - acc: 0.8962
- val_loss: 0.1332 - val_acc: 0.9567
Epoch 2/20
60000/60000 [==============================] - 6s 99us/step - loss: 0.1713 - acc: 0.9481
- val_loss: 0.0953 - val_acc: 0.9702
Epoch 3/20
60000/60000 [==============================] - 6s 100us/step - loss: 0.1265 - acc: 0.9623
- val_loss: 0.0868 - val_acc: 0.9726
Epoch 4/20
60000/60000 [==============================] - 6s 100us/step - loss: 0.1040 - acc: 0.9677
- val_loss: 0.0798 - val_acc: 0.9739
Epoch 5/20
60000/60000 [==============================] - 6s 100us/step - loss: 0.0876 - acc: 0.9735
- val_loss: 0.0689 - val_acc: 0.9787
Epoch 6/20
60000/60000 [==============================] - 6s 99us/step - loss: 0.0743 - acc: 0.9771
- val_loss: 0.0655 - val_acc: 0.9795
Epoch 7/20
60000/60000 [==============================] - 6s 100us/step - loss: 0.0653 - acc: 0.9792
- val_loss: 0.0637 - val_acc: 0.9815
Epoch 8/20
60000/60000 [==============================] - 6s 100us/step - loss: 0.0590 - acc: 0.9811
- val_loss: 0.0681 - val_acc: 0.9799
Epoch 9/20
60000/60000 [==============================] - 6s 101us/step - loss: 0.0509 - acc: 0.9836
- val_loss: 0.0589 - val_acc: 0.9831
Epoch 10/20
60000/60000 [==============================] - 6s 100us/step - loss: 0.0469 - acc: 0.9844
- val_loss: 0.0624 - val_acc: 0.9826
Epoch 11/20
60000/60000 [==============================] - 6s 99us/step - loss: 0.0410 - acc: 0.9868
- val_loss: 0.0606 - val_acc: 0.9814
Epoch 12/20
60000/60000 [==============================] - 6s 100us/step - loss: 0.0391 - acc: 0.9874
- val_loss: 0.0587 - val_acc: 0.9825
Epoch 13/20
60000/60000 [==============================] - 6s 101us/step - loss: 0.0366 - acc: 0.9878
- val_loss: 0.0597 - val_acc: 0.9827
Epoch 14/20
60000/60000 [==============================] - 6s 103us/step - loss: 0.0328 - acc: 0.9892
- val_loss: 0.0630 - val_acc: 0.9825
Epoch 15/20
60000/60000 [==============================] - 6s 101us/step - loss: 0.0327 - acc: 0.9895
- val_loss: 0.0623 - val_acc: 0.9825
Epoch 16/20
60000/60000 [==============================] - 6s 100us/step - loss: 0.0294 - acc: 0.9899
- val_loss: 0.0614 - val_acc: 0.9839
Epoch 17/20
60000/60000 [==============================] - 6s 102us/step - loss: 0.0277 - acc: 0.9908
- val_loss: 0.0606 - val_acc: 0.9833
Epoch 18/20
60000/60000 [==============================] - 6s 106us/step - loss: 0.0237 - acc: 0.9919
- val_loss: 0.0602 - val_acc: 0.9840
Epoch 19/20
60000/60000 [==============================] - 6s 106us/step - loss: 0.0269 - acc: 0.9911
- val_loss: 0.0591 - val_acc: 0.9840
Epoch 20/20
60000/60000 [==============================] - 6s 101us/step - loss: 0.0220 - acc: 0.9925
- val_loss: 0.0598 - val_acc: 0.9839
```

In [53]:

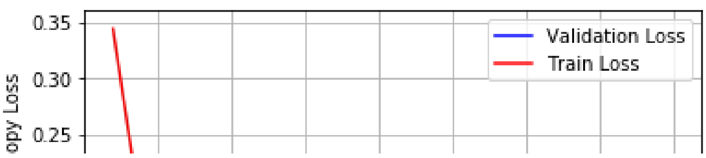
```
model6.summary()
```

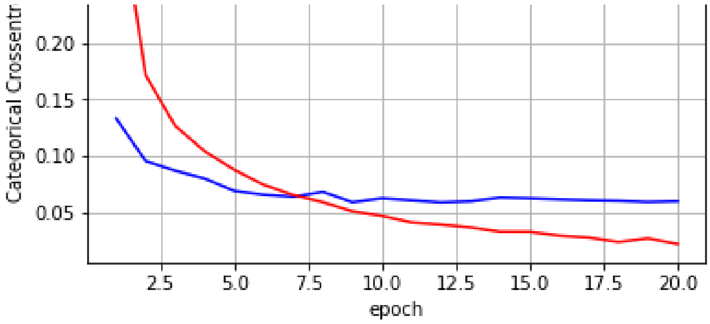
```
Model: "sequential_10"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_37 (Dense)             (None, 512)               401920    
_________________________________________________________________
batch_normalization_13 (Batc (None, 512)               2048      
_________________________________________________________________
dropout_22 (Dropout)         (None, 512)               0         
_________________________________________________________________
dense_38 (Dense)             (None, 256)               131328    
_________________________________________________________________
batch_normalization_14 (Batc (None, 256)               1024      
_________________________________________________________________
dropout_23 (Dropout)         (None, 256)               0         
_________________________________________________________________
dense_39 (Dense)             (None, 128)               32896     
_________________________________________________________________
batch_normalization_15 (Batc (None, 128)               512       
_________________________________________________________________
dropout_24 (Dropout)         (None, 128)               0         
_________________________________________________________________
dense_40 (Dense)             (None, 10)                1290      
=================================================================
Total params: 571,018
Trainable params: 569,226
Non-trainable params: 1,792
_________________________________________________________________
```

In [54]:

```
score = model6.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

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

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

# print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verb
ose=1, validation_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 epoc
hs

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

```
Test score: 0.059768225400491794
Test accuracy: 0.9839
```

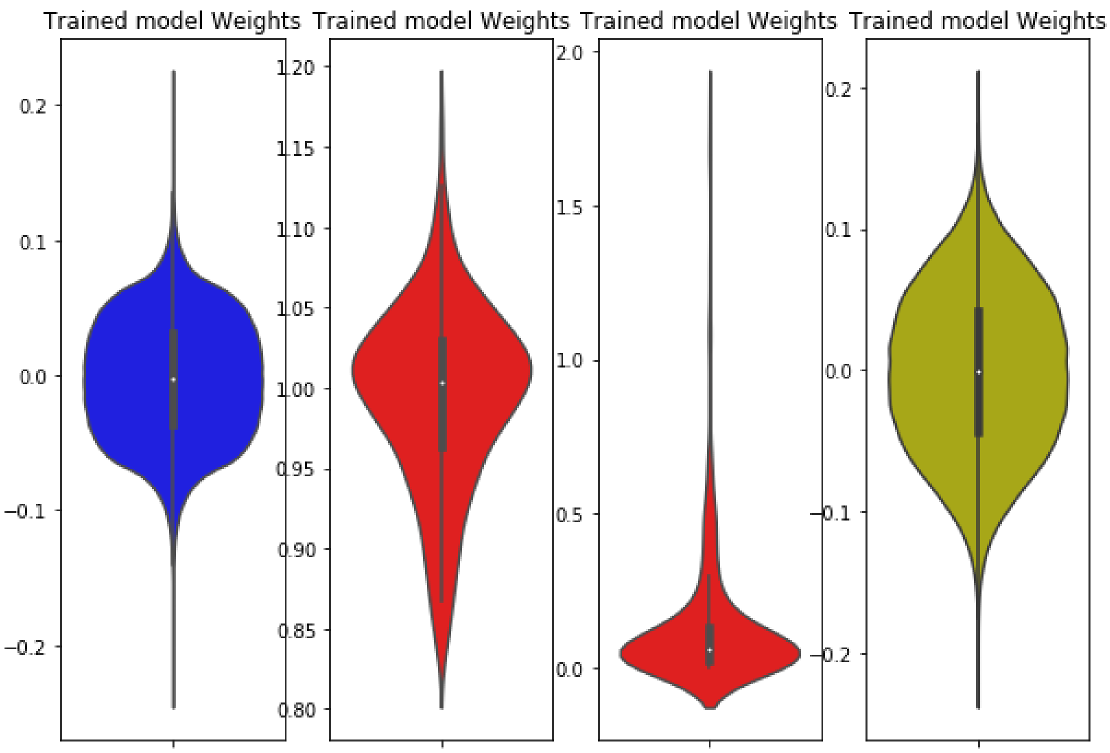




The little value of dropout made the model to overfit at 7th epoch.But the stats are good till the end.

In [55]:

```
w_after = model6.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=(10,7))
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='r')
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()
```



Hidden Layer 1 Hidden Layer 2 Hidden Layer 3 Output Layer

6.3 RELU ACTIVATION WITH BATCH NORM (Optimiser-Adamax)

In [0]:

```
from keras.layers.normalization import BatchNormalization
model6 = Sequential()

model6.add(Dense(512, input_dim=input_dim, activation='relu'))
model6.add(BatchNormalization())

model6.add(Dense(256, input_dim=input_dim, activation='relu'))
model6.add(BatchNormalization())

model6.add(Dense(128, input_dim=input_dim, activation='relu'))
model6.add(BatchNormalization())

model6.add(Dense(10, input_dim=input_dim, activation='softmax'))
```

In [57]:

```
model6.compile(optimizer='Adamax', loss='categorical_crossentropy', metrics=['accuracy']
)

history = model6.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1
, validation_data=(X_test, Y_test))
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 8s 128us/step - loss: 0.1790 - acc: 0.9464
- val_loss: 0.0975 - val_acc: 0.9699
Epoch 2/20
60000/60000 [==============================] - 6s 100us/step - loss: 0.0691 - acc: 0.9797
- val_loss: 0.0835 - val_acc: 0.9722
Epoch 3/20
60000/60000 [==============================] - 6s 98us/step - loss: 0.0420 - acc: 0.9873
- val_loss: 0.0815 - val_acc: 0.9735
Epoch 4/20
60000/60000 [==============================] - 6s 97us/step - loss: 0.0276 - acc: 0.9918
- val_loss: 0.0720 - val_acc: 0.9775
Epoch 5/20
60000/60000 [==============================] - 6s 97us/step - loss: 0.0171 - acc: 0.9949
- val_loss: 0.0656 - val_acc: 0.9791
Epoch 6/20
60000/60000 [==============================] - 6s 99us/step - loss: 0.0122 - acc: 0.9964
- val_loss: 0.0793 - val_acc: 0.9768
Epoch 7/20
60000/60000 [==============================] - 6s 98us/step - loss: 0.0109 - acc: 0.9966
- val_loss: 0.0704 - val_acc: 0.9812
Epoch 8/20
60000/60000 [==============================] - 6s 97us/step - loss: 0.0074 - acc: 0.9979
- val_loss: 0.0691 - val_acc: 0.9801
Epoch 9/20
60000/60000 [==============================] - 6s 97us/step - loss: 0.0062 - acc: 0.9982
- val_loss: 0.0670 - val_acc: 0.9809
Epoch 10/20
60000/60000 [==============================] - 6s 99us/step - loss: 0.0042 - acc: 0.9989
- val_loss: 0.0686 - val_acc: 0.9804
Epoch 11/20
60000/60000 [==============================] - 6s 99us/step - loss: 0.0040 - acc: 0.9991
- val_loss: 0.0680 - val_acc: 0.9820
Epoch 12/20
60000/60000 [==============================] - 6s 98us/step - loss: 0.0036 - acc: 0.9991
- val_loss: 0.0753 - val_acc: 0.9795
Epoch 13/20
60000/60000 [==============================] - 6s 97us/step - loss: 0.0030 - acc: 0.9993
- val_loss: 0.0701 - val_acc: 0.9806
Epoch 14/20
60000/60000 [==============================] - 6s 98us/step - loss: 0.0031 - acc: 0.9991
- val_loss: 0.0673 - val_acc: 0.9820
```

```
Epoch 15/20
60000/60000 [==============================] - 6s 99us/step - loss: 0.0035 - acc: 0.9990
- val_loss: 0.0732 - val_acc: 0.9816
Epoch 16/20
60000/60000 [==============================] - 6s 98us/step - loss: 0.0032 - acc: 0.9990
- val_loss: 0.0766 - val_acc: 0.9803
Epoch 17/20
60000/60000 [==============================] - 6s 98us/step - loss: 0.0016 - acc: 0.9997
- val_loss: 0.0681 - val_acc: 0.9833
Epoch 18/20
60000/60000 [==============================] - 6s 100us/step - loss: 0.0021 - acc: 0.9995
- val_loss: 0.0702 - val_acc: 0.9822
Epoch 19/20
60000/60000 [==============================] - 6s 100us/step - loss: 0.0026 - acc: 0.9992
- val_loss: 0.0727 - val_acc: 0.9820
Epoch 20/20
60000/60000 [==============================] - 6s 97us/step - loss: 0.0023 - acc: 0.9994
- val_loss: 0.0755 - val_acc: 0.9828
```

In [58]:

```
model6.summary()
```

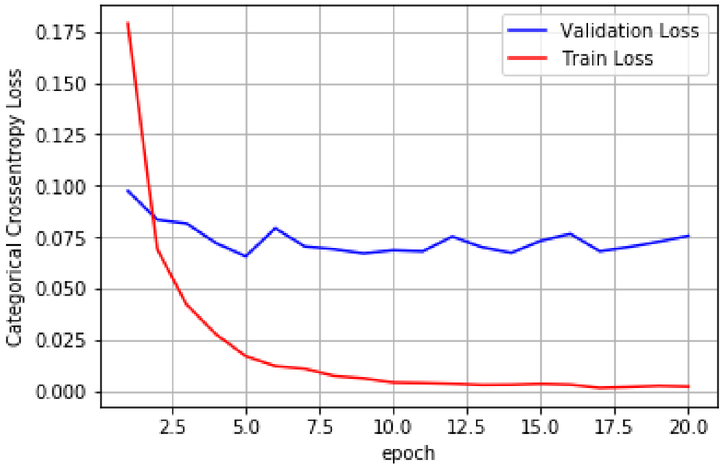
```
Model: "sequential_11"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_41 (Dense)             (None, 512)               401920    
_________________________________________________________________
batch_normalization_16 (Batc (None, 512)               2048      
_________________________________________________________________
dense_42 (Dense)             (None, 256)               131328    
_________________________________________________________________
batch_normalization_17 (Batc (None, 256)               1024      
_________________________________________________________________
dense_43 (Dense)             (None, 128)               32896     
_________________________________________________________________
batch_normalization_18 (Batc (None, 128)               512       
_________________________________________________________________
dense_44 (Dense)             (None, 10)                1290      
=================================================================
Total params: 571,018
Trainable params: 569,226
Non-trainable params: 1,792
_________________________________________________________________
```

In [59]:

```
score = model6.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

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

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

# print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verb
ose=1, validation_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 epoc
hs
```

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

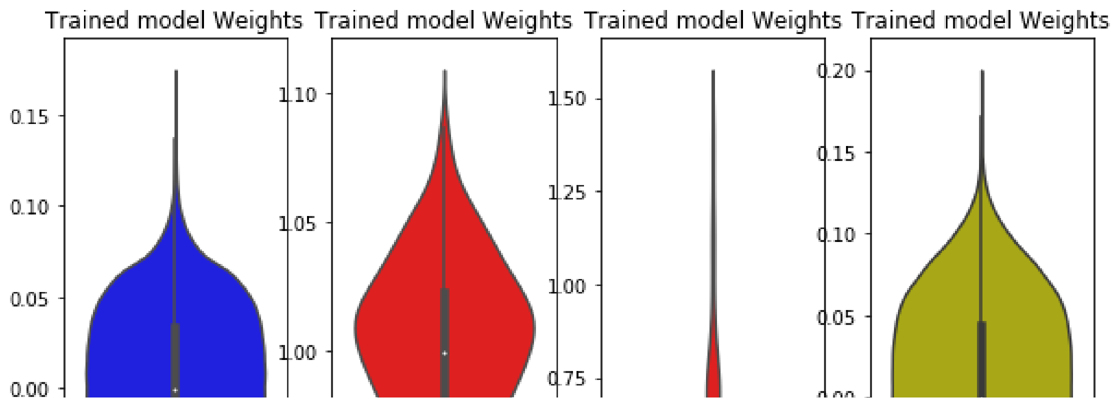
```
Test score: 0.0755472852376839
Test accuracy: 0.9828
```

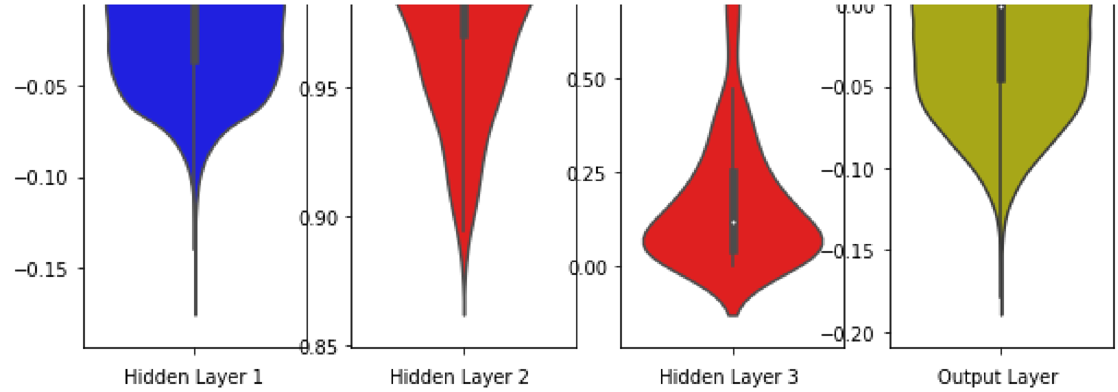


Overfitting has seen in the earlier epochs.

In [60]:

```
w_after = model6.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=(10,7))
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='r')
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()
```





In [0]:

```python
from prettytable import PrettyTable
F='Not present'
T='Present'
Model = ["2","2","2","2","2","3","3","3","3","5","5","5","5"]
test_scr=[0.08,0.09,0.06,0.08,0.06,0.108,0.06,0.07,0.05,0.08,0.07,0.10,0.06]
test_acc=[0.98,0.98,0.98,0.97,0.98,0.97,0.98,0.98,0.98,0.98,0.98,0.97,0.98]
d=[F,F,T,F,T,F,T,F,T,F,T,F,T]
b=[F,F,F,T,T,F,F,T,T,F,F,T,T]
sno =[1,2,3,4,5,6,7,8,9,10,11,12,13]
table = PrettyTable()
table.add_column('S-NO',sno)
table.add_column("Layers",Model)
table.add_column("Test Loss",test_scr)
table.add_column("Test Acuracy",test_acc)
table.add_column("Dropout Present",d)
table.add_column("Batch Norm Present",b)
```

In [0]:

```python
print(table)
print('Dropout is 0.5 in all models')
```

```
+------+--------+-----------+-------------+-----------------+--------------------+
| S-NO | Layers | Test Loss | Test Acuracy | Dropout Present | Batch Norm Present |
+------+--------+-----------+-------------+-----------------+--------------------+
|  1   |   2    |    0.08   |     0.98    |   Not present   |    Not present     |
|  2   |   2    |    0.09   |     0.98    |   Not present   |    Not present     |
|  3   |   2    |    0.06   |     0.98    |     Present     |    Not present     |
|  4   |   2    |    0.08   |     0.97    |   Not present   |      Present       |
|  5   |   2    |    0.06   |     0.98    |     Present     |      Present       |
|  6   |   3    |   0.108   |     0.97    |   Not present   |    Not present     |
|  7   |   3    |    0.06   |     0.98    |     Present     |    Not present     |
|  8   |   3    |    0.07   |     0.98    |   Not present   |      Present       |
|  9   |   3    |    0.05   |     0.98    |     Present     |      Present       |
|  10  |   5    |    0.08   |     0.98    |   Not present   |    Not present     |
|  11  |   5    |    0.07   |     0.98    |     Present     |    Not present     |
|  12  |   5    |    0.1    |     0.97    |   Not present   |      Present       |
|  13  |   5    |    0.06   |     0.98    |     Present     |      Present       |
+------+--------+-----------+-------------+-----------------+--------------------+
Dropout is 0.5 in all models
```

In [0]:

```python
from prettytable import PrettyTable
F='Not present'
T='Present'
T5='Present (Value=0.5)'
T3='Present (Value=0.3)'
T4='Present (Value=0.4)'
Optimiser = ["RMSprop","RMSprop","RMSprop","SGD","SGD","SGD","Adamax","Adamax","Adamax"]
test_scr=[0.114,0.05,0.103,0.135,0.07,0.082,0.065,0.059,0.075]
test_acc=[0.979,0.985,0.979,0.959,0.976,0.974,0.983,0.983,0.982]
d=[T5,T3,F,T4,T3,F,T5,T3,F]
b=[F,T,T,F,T,T,F,T,T]
sno =[1,2,3,4,5,6,7,8,9]
```

```
table = PrettyTable()
table.add_column('S-NO',sno)
table.add_column("Optimizer",Optimiser)
table.add_column("Test Loss",test_scr)
table.add_column("Test Acuracy",test_acc)
table.add_column("Dropout Present",d)
table.add_column("Batch Norm Present",b)
```

In [62]:

```
print('Pretty table of models with different optimizers other than ADAM')
print(table)
```

```
Pretty table of models with different optimizers other than ADAM
+------+-----------+-----------+--------------+---------------------+------------------
--+
| S-NO | Optimizer | Test Loss | Test Acuracy |   Dropout Present   | Batch Norm Present
|
+------+-----------+-----------+--------------+---------------------+------------------
--+
|  1   |  RMSprop  |   0.114   |    0.979     | Present (Value=0.5) |    Not present
|
|  2   |  RMSprop  |    0.05   |    0.985     | Present (Value=0.3) |      Present
|
|  3   |  RMSprop  |   0.103   |    0.979     |     Not present     |      Present
|
|  4   |    SGD    |   0.135   |    0.959     | Present (Value=0.4) |    Not present
|
|  5   |    SGD    |    0.07   |    0.976     | Present (Value=0.3) |      Present
|
|  6   |    SGD    |   0.082   |    0.974     |     Not present     |      Present
|
|  7   |   Adamax  |   0.065   |    0.983     | Present (Value=0.5) |    Not present
|
|  8   |   Adamax  |   0.059   |    0.983     | Present (Value=0.3) |      Present
|
|  9   |   Adamax  |   0.075   |    0.982     |     Not present     |      Present
|
+------+-----------+-----------+--------------+---------------------+------------------
--+
```

Models with RMSprop and Adamax as their optimizers gave better Test Accuracy.

Conclusions

1. Naive models (without dropout or batch norm) failed as they ended up in overfitting and higher validation loss.

2. Dropout has clearly played a vital role in minimising the validation loss to as low as training loss after the last epoch.

3. Models with Batch normalisation with no dropout failed in having a lower validation loss.

4. Droput with batch norm models were also good.

5. Models with RMSprop optimiser gave splendid results than all other models.

6. SGD optimiser models started with low accuracy and higher loss values but in the end they delivered better results. If they ran for 25 - 30 epochs ,they may achieve similar stats of best models mentioned here.