

Keras -- MLPs on MNIST

```
In [0]: 1 import tensorflow.compat.v1 as tf
        2 tf.disable_v2_behavior()
```

```
In [0]: 1 # if you keras is not using tensorflow as backend set "KERAS_BACKEND=tensorflow" use this command
        2 from keras.utils import np_utils
        3 from keras.datasets import mnist
        4 import seaborn as sns
        5 from keras.initializers import RandomNormal, he_normal
        6 from keras.layers.normalization import BatchNormalization
        7 from keras.layers import Dropout
```

```
In [0]: 1 %matplotlib inline
        2 #%matplotlib
        3 #%matplotlib nbagg
        4 import matplotlib.pyplot as plt
        5 import numpy as np
        6 import time
        7 # https://gist.github.com/greydanus/f6eee59eaf1d90fcb3b534a25362cea4
        8 # https://stackoverflow.com/a/14434334
        9 # this function is used to update the plots for each epoch and error
       10 def plt_dynamic(x, vy, ty, ax, colors=['b']):
       11     ax.plot(x, ty, 'r', label="Train Loss")
       12     ax.plot(x, vy, 'b', label="Validation Loss")
       13     plt.legend()
       14     plt.grid()
       15     fig.canvas.draw()
       16     plt.show()
```

```
In [0]: 1 # the data, shuffled and split between train and test sets
        2 (X_train, y_train), (X_test, y_test) = mnist.load_data()
```

```
In [45]: 1 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]))
        2 print("Number of test 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 test examples : 10000 and each image is of shape (28, 28)

In [0]:

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

```
In [47]: 1 print("Number of training examples :", X_train.shape[0], "and each image is of shape (%d)"%(X_train.shape[1]))
2 print("Number of test examples :", X_test.shape[0], "and each image is of shape (%d)"%(X_test.shape[1]))
3 print(X_train[0])
```

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

Number of test examples : 10000 and each image is of shape (784)

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

0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0]								

```
In [48]: 1 X_train = X_train/255
          2 X_test = X_test/255
          3 print(X_train[0])
```

[illegible]

```
In [49]: 1 print("Class label of first image :", y_train[0])
          2 Y_train = np_utils.to_categorical(y_train, 10)
          3 Y_test = np_utils.to_categorical(y_test, 10)
          4 print("After converting the output into a vector : ",Y_train[0])
```

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

Softmax classifier

```
In [0]: 1 # https://keras.io/getting-started/sequential-model-guide/
2 # https://keras.io/layers/core/
3 # https://keras.io/activations/
4
5 from keras.models import Sequential
6 from keras.layers import Dense, Activation
```

```
In [0]: 1 # some model parameters
2 output_dim = 10
3 input_dim = X_train.shape[1]
4 batch_size = 128
5 nb_epoch = 22
```

2 hidden layer - MLP with Batch normalization and Dropout(0.5)

```
In [52]: 1 %%time
2 model_relu = Sequential()
3 model_relu.add(Dense(430, activation='relu', input_shape=(input_dim,), kernel_initializer=he_normal(seed=None)))
4 model_relu.add(BatchNormalization())
5 model_relu.add(Dropout(0.5))
6 model_relu.add(Dense(322, activation='relu', kernel_initializer=he_normal(seed=None)))
7 model_relu.add(BatchNormalization())
8 model_relu.add(Dropout(0.5))
9 model_relu.add(Dense(output_dim, activation='softmax'))
10
11 print(model_relu.summary())
12
13 model_relu.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
14
15 history = model_relu.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, validation_data=(X_test, Y_test))
```

Model: "sequential_10"

Layer (type)	Output Shape	Param #
=====		
dense_40 (Dense)	(None, 430)	337550
batch_normalization_31 (Batch Normalization)	(None, 430)	1720
dropout_31 (Dropout)	(None, 430)	0
dense_41 (Dense)	(None, 322)	138782
batch_normalization_32 (Batch Normalization)	(None, 322)	1288
dropout_32 (Dropout)	(None, 322)	0
dense_42 (Dense)	(None, 10)	3230
=====		
Total params: 482,570		
Trainable params: 481,066		
Non-trainable params: 1,504		

None

Train on 60000 samples, validate on 10000 samples

Epoch 1/22

60000/60000 [=====] - 6s 96us/step - loss: 0.4084 - acc: 0.8767 - val_loss: 0.1316 - val_acc: 0.9579

Epoch 2/22

60000/60000 [=====] - 3s 57us/step - loss: 0.1966 - acc: 0.9399 - val_loss: 0.1040 - val_acc: 0.9679

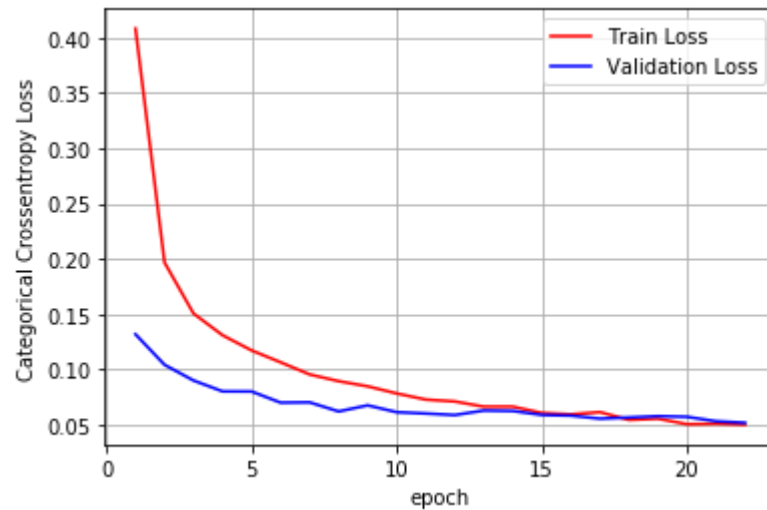
Epoch 3/22

```
60000/60000 [=====] - 4s 59us/step - loss: 0.1504 - acc: 0.9532 - val_loss: 0.0897 - val_acc: 0.9723
Epoch 4/22
60000/60000 [=====] - 4s 59us/step - loss: 0.1307 - acc: 0.9600 - val_loss: 0.0799 - val_acc: 0.9748
Epoch 5/22
60000/60000 [=====] - 3s 57us/step - loss: 0.1170 - acc: 0.9634 - val_loss: 0.0798 - val_acc: 0.9751
Epoch 6/22
60000/60000 [=====] - 3s 56us/step - loss: 0.1062 - acc: 0.9666 - val_loss: 0.0697 - val_acc: 0.9769
Epoch 7/22
60000/60000 [=====] - 3s 58us/step - loss: 0.0952 - acc: 0.9703 - val_loss: 0.0700 - val_acc: 0.9786
Epoch 8/22
60000/60000 [=====] - 3s 56us/step - loss: 0.0891 - acc: 0.9716 - val_loss: 0.0617 - val_acc: 0.9804
Epoch 9/22
60000/60000 [=====] - 4s 59us/step - loss: 0.0845 - acc: 0.9738 - val_loss: 0.0672 - val_acc: 0.9792
Epoch 10/22
60000/60000 [=====] - 4s 59us/step - loss: 0.0780 - acc: 0.9751 - val_loss: 0.0610 - val_acc: 0.9818
Epoch 11/22
60000/60000 [=====] - 3s 58us/step - loss: 0.0725 - acc: 0.9769 - val_loss: 0.0599 - val_acc: 0.9820
Epoch 12/22
60000/60000 [=====] - 4s 59us/step - loss: 0.0708 - acc: 0.9777 - val_loss: 0.0585 - val_acc: 0.9826
Epoch 13/22
60000/60000 [=====] - 3s 57us/step - loss: 0.0660 - acc: 0.9776 - val_loss: 0.0625 - val_acc: 0.9809
Epoch 14/22
60000/60000 [=====] - 3s 57us/step - loss: 0.0661 - acc: 0.9785 - val_loss: 0.0622 - val_acc: 0.9816
Epoch 15/22
60000/60000 [=====] - 4s 59us/step - loss: 0.0604 - acc: 0.9804 - val_loss: 0.0586 - val_acc: 0.9837
Epoch 16/22
60000/60000 [=====] - 3s 56us/step - loss: 0.0591 - acc: 0.9804 - val_loss: 0.0580 - val_acc: 0.9837
Epoch 17/22
60000/60000 [=====] - 3s 58us/step - loss: 0.0611 - acc: 0.9801 - val_loss: 0.0552 - val_acc: 0.9837
Epoch 18/22
60000/60000 [=====] - 3s 55us/step - loss: 0.0541 - acc: 0.9824 - val_loss: 0.0563 - val_acc: 0.9842
Epoch 19/22
60000/60000 [=====] - 3s 56us/step - loss: 0.0552 - acc: 0.9827 - val_loss: 0.0574 - val_acc: 0.9843
Epoch 20/22
60000/60000 [=====] - 3s 57us/step - loss: 0.0502 - acc: 0.9838 - val_loss: 0.0569 - val_acc: 0.9839
Epoch 21/22
60000/60000 [=====] - 4s 59us/step - loss: 0.0506 - acc: 0.9835 - val_loss: 0.0528 - val_acc: 0.9841
Epoch 22/22
60000/60000 [=====] - 4s 58us/step - loss: 0.0498 - acc: 0.9838 - val_loss: 0.0515 - val_acc: 0.9856
CPU times: user 1min 37s, sys: 7.86 s, total: 1min 45s
Wall time: 1min 19s
```

```
In [53]: 1 score = model_relu.evaluate(X_test, Y_test, verbose=0)
2 print('Test score:', score[0])
3 print('Test accuracy:', score[1])
4 fig, ax = plt.subplots(1,1)
5 ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')
6
7 # list of epoch numbers
8 x = list(range(1,nb_epoch+1))
9
10 vy = history.history['val_loss']
11 ty = history.history['loss']
12 plt_dynamic(x, vy, ty, ax)
```

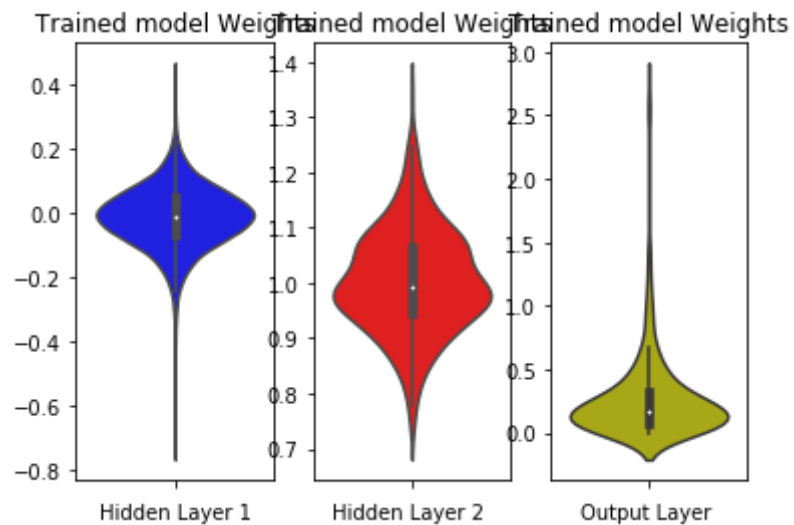
Test score: 0.051465931210145935

Test accuracy: 0.9856



In [54]:

```
1 %%time
2 w_after = model_relu.get_weights()
3
4 h1_w = w_after[0].flatten().reshape(-1,1)
5 h2_w = w_after[2].flatten().reshape(-1,1)
6 out_w = w_after[4].flatten().reshape(-1,1)
7
8 fig = plt.figure()
9 plt.title("Weight matrices after model trained")
10 plt.subplot(1, 3, 1)
11 plt.title("Trained model Weights")
12 ax = sns.violinplot(y=h1_w,color='b')
13 plt.xlabel('Hidden Layer 1')
14
15 plt.subplot(1, 3, 2)
16 plt.title("Trained model Weights")
17 ax = sns.violinplot(y=h2_w, color='r')
18 plt.xlabel('Hidden Layer 2 ')
19
20 plt.subplot(1, 3, 3)
21 plt.title("Trained model Weights")
22 ax = sns.violinplot(y=out_w,color='y')
23 plt.xlabel('Output Layer ')
24 plt.show()
```



3 hidden layer - MLP with Batch normalization and Dropout(0.5)

In [55]:

```
1 %%time
2 model_relu = Sequential()
3 model_relu.add(Dense(320, activation='relu', input_shape=(input_dim,), kernel_initializer=he_normal(seed=None)))
4 model_relu.add(BatchNormalization())
5 model_relu.add(Dropout(0.5))
6 model_relu.add(Dense(270, activation='relu', kernel_initializer=he_normal(seed=None)) )
7 model_relu.add(BatchNormalization())
8 model_relu.add(Dropout(0.5))
9 model_relu.add(Dense(162, activation='relu', input_shape=(input_dim,), kernel_initializer=he_normal(seed=None)))
10 model_relu.add(BatchNormalization())
11 model_relu.add(Dropout(0.5))
12 model_relu.add(Dense(output_dim, activation='softmax'))
13
14 print(model_relu.summary())
15
16 model_relu.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
17
18 history = model_relu.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, validation_data=(X_test, Y_test))
```

Model: "sequential_11"

Layer (type)	Output Shape	Param #
=====		
dense_43 (Dense)	(None, 320)	251200
batch_normalization_33 (Batch Normalization)	(None, 320)	1280
dropout_33 (Dropout)	(None, 320)	0
dense_44 (Dense)	(None, 270)	86670
batch_normalization_34 (Batch Normalization)	(None, 270)	1080
dropout_34 (Dropout)	(None, 270)	0
dense_45 (Dense)	(None, 162)	43902
batch_normalization_35 (Batch Normalization)	(None, 162)	648
dropout_35 (Dropout)	(None, 162)	0
dense_46 (Dense)	(None, 10)	1630
=====		
Total params: 386,410		
Trainable params: 384,906		

Non-trainable params: 1,504

None

Train on 60000 samples, validate on 10000 samples

Epoch 1/22

60000/60000 [=====] - 7s 115us/step - loss: 0.6269 - acc: 0.8051 - val_loss: 0.1738 - val_acc: 0.9466

Epoch 2/22

60000/60000 [=====] - 4s 67us/step - loss: 0.2746 - acc: 0.9184 - val_loss: 0.1327 - val_acc: 0.9583

Epoch 3/22

60000/60000 [=====] - 4s 68us/step - loss: 0.2140 - acc: 0.9364 - val_loss: 0.1081 - val_acc: 0.9651

Epoch 4/22

60000/60000 [=====] - 4s 71us/step - loss: 0.1834 - acc: 0.9457 - val_loss: 0.0949 - val_acc: 0.9705

Epoch 5/22

60000/60000 [=====] - 4s 68us/step - loss: 0.1573 - acc: 0.9532 - val_loss: 0.0908 - val_acc: 0.9708

Epoch 6/22

60000/60000 [=====] - 4s 67us/step - loss: 0.1418 - acc: 0.9573 - val_loss: 0.0824 - val_acc: 0.9752

Epoch 7/22

60000/60000 [=====] - 4s 67us/step - loss: 0.1276 - acc: 0.9618 - val_loss: 0.0787 - val_acc: 0.9757

Epoch 8/22

60000/60000 [=====] - 4s 69us/step - loss: 0.1192 - acc: 0.9641 - val_loss: 0.0758 - val_acc: 0.9768

Epoch 9/22

60000/60000 [=====] - 4s 71us/step - loss: 0.1159 - acc: 0.9652 - val_loss: 0.0706 - val_acc: 0.9784

Epoch 10/22

60000/60000 [=====] - 4s 68us/step - loss: 0.1067 - acc: 0.9674 - val_loss: 0.0740 - val_acc: 0.9768

Epoch 11/22

60000/60000 [=====] - 4s 69us/step - loss: 0.1051 - acc: 0.9670 - val_loss: 0.0675 - val_acc: 0.9792

Epoch 12/22

60000/60000 [=====] - 4s 69us/step - loss: 0.0980 - acc: 0.9701 - val_loss: 0.0737 - val_acc: 0.9776

Epoch 13/22

60000/60000 [=====] - 4s 71us/step - loss: 0.0965 - acc: 0.9708 - val_loss: 0.0619 - val_acc: 0.9807

Epoch 14/22

60000/60000 [=====] - 4s 69us/step - loss: 0.0909 - acc: 0.9724 - val_loss: 0.0616 - val_acc: 0.9826

Epoch 15/22

60000/60000 [=====] - 4s 67us/step - loss: 0.0856 - acc: 0.9738 - val_loss: 0.0665 - val_acc: 0.9795

Epoch 16/22

60000/60000 [=====] - 4s 68us/step - loss: 0.0866 - acc: 0.9736 - val_loss: 0.0630 - val_acc: 0.9816

Epoch 17/22

60000/60000 [=====] - 4s 67us/step - loss: 0.0814 - acc: 0.9750 - val_loss: 0.0680 - val_acc: 0.9806

Epoch 18/22

60000/60000 [=====] - 4s 68us/step - loss: 0.0797 - acc: 0.9750 - val_loss: 0.0661 - val_acc: 0.9813

Epoch 19/22

60000/60000 [=====] - 4s 68us/step - loss: 0.0778 - acc: 0.9760 - val_loss: 0.0618 - val_acc: 0.9818

Epoch 20/22

60000/60000 [=====] - 4s 67us/step - loss: 0.0745 - acc: 0.9768 - val_loss: 0.0621 - val_acc: 0.9822

Epoch 21/22

60000/60000 [=====] - 4s 69us/step - loss: 0.0711 - acc: 0.9779 - val_loss: 0.0622 - val_acc: 0.9827

Epoch 22/22

60000/60000 [=====] - 4s 66us/step - loss: 0.0700 - acc: 0.9790 - val_loss: 0.0603 - val_acc: 0.9820

CPU times: user 1min 59s, sys: 9.78 s, total: 2min 9s

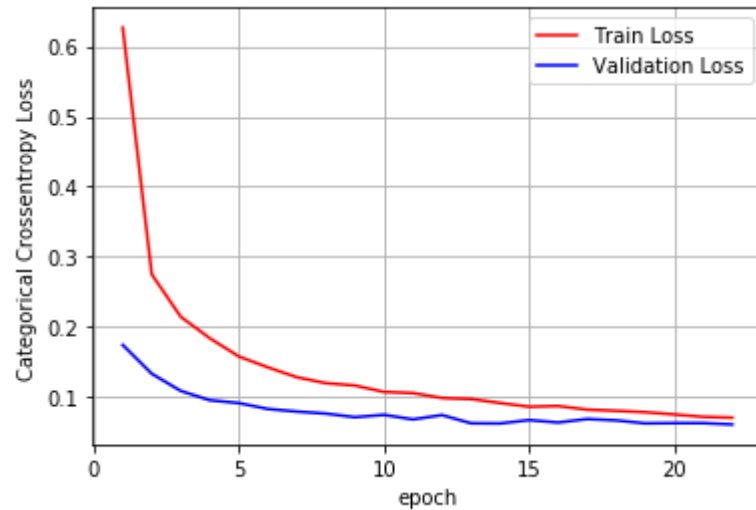
Wall time: 1min 34s

In [56]:

```
1 score = model_relu.evaluate(X_test, Y_test, verbose=0)
2 print('Test score:', score[0])
3 print('Test accuracy:', score[1])
4
5 fig,ax = plt.subplots(1,1)
6 ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')
7
8 # List of epoch numbers
9 x = list(range(1,nb_epoch+1))
10
11 vy = history.history['val_loss']
12 ty = history.history['loss']
13 plt_dynamic(x, vy, ty, ax)
```

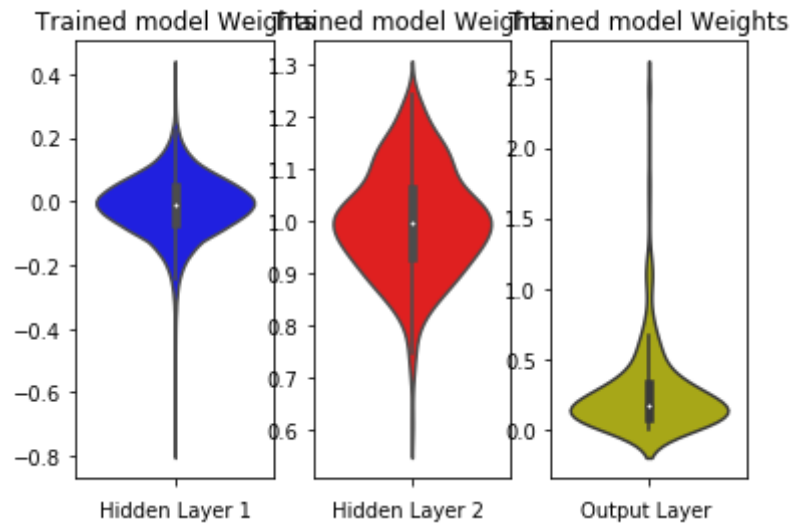
Test score: 0.06025076956005068

Test accuracy: 0.982



In [57]:

```
1 %%time
2 w_after = model_relu.get_weights()
3
4 h1_w = w_after[0].flatten().reshape(-1,1)
5 h2_w = w_after[2].flatten().reshape(-1,1)
6 out_w = w_after[4].flatten().reshape(-1,1)
7
8 fig = plt.figure()
9 plt.title("Weight matrices after model trained")
10 plt.subplot(1, 3, 1)
11 plt.title("Trained model Weights")
12 ax = sns.violinplot(y=h1_w,color='b')
13 plt.xlabel('Hidden Layer 1')
14
15 plt.subplot(1, 3, 2)
16 plt.title("Trained model Weights")
17 ax = sns.violinplot(y=h2_w, color='r')
18 plt.xlabel('Hidden Layer 2 ')
19
20 plt.subplot(1, 3, 3)
21 plt.title("Trained model Weights")
22 ax = sns.violinplot(y=out_w,color='y')
23 plt.xlabel('Output Layer ')
24 plt.show()
```



5 hidden layer - MLP with Batch normalization and Dropout(0.5)

In [58]:

```
1 %%time
2 model_relu = Sequential()
3 model_relu.add(Dense(340, activation='relu', input_shape=(input_dim,), kernel_initializer=he_normal(seed=None)))
4 model_relu.add(BatchNormalization())
5 model_relu.add(Dropout(0.5))
6 model_relu.add(Dense(190, activation='relu', kernel_initializer=he_normal(seed=None)) )
7 model_relu.add(BatchNormalization())
8 model_relu.add(Dropout(0.5))
9 model_relu.add(Dense(112, activation='relu', kernel_initializer=he_normal(seed=None)))
10 model_relu.add(BatchNormalization())
11 model_relu.add(Dropout(0.5))
12 model_relu.add(Dense(72, activation='relu', kernel_initializer=he_normal(seed=None)))
13 model_relu.add(BatchNormalization())
14 model_relu.add(Dropout(0.5))
15 model_relu.add(Dense(38, activation='relu', kernel_initializer=he_normal(seed=None)))
16 model_relu.add(BatchNormalization())
17 model_relu.add(Dropout(0.5))
18 model_relu.add(Dense(output_dim, activation='softmax'))
19
20 print(model_relu.summary())
21
22 model_relu.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
23
24 history = model_relu.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, validation_data=(X_test, Y_test))
```

Model: "sequential_12"

Layer (type)	Output Shape	Param #
=====		
dense_47 (Dense)	(None, 340)	266900
<hr/>		
batch_normalization_36 (Batch Normalization)	(None, 340)	1360
<hr/>		
dropout_36 (Dropout)	(None, 340)	0
<hr/>		
dense_48 (Dense)	(None, 190)	64790
<hr/>		
batch_normalization_37 (Batch Normalization)	(None, 190)	760
<hr/>		
dropout_37 (Dropout)	(None, 190)	0
<hr/>		
dense_49 (Dense)	(None, 112)	21392
<hr/>		
batch_normalization_38 (Batch Normalization)	(None, 112)	448
<hr/>		

dropout_38 (Dropout)	(None, 112)	0
dense_50 (Dense)	(None, 72)	8136
batch_normalization_39 (Batch Normalization)	(None, 72)	288
dropout_39 (Dropout)	(None, 72)	0
dense_51 (Dense)	(None, 38)	2774
batch_normalization_40 (Batch Normalization)	(None, 38)	152
dropout_40 (Dropout)	(None, 38)	0
dense_52 (Dense)	(None, 10)	390

=====
Total params: 367,390
Trainable params: 365,886
Non-trainable params: 1,504

None

Train on 60000 samples, validate on 10000 samples

Epoch 1/22

60000/60000 [=====] - 9s 151us/step - loss: 1.5619 - acc: 0.4815 - val_loss: 0.4524 - val_acc: 0.8852

Epoch 2/22

60000/60000 [=====] - 5s 91us/step - loss: 0.6659 - acc: 0.7948 - val_loss: 0.2386 - val_acc: 0.9382

Epoch 3/22

60000/60000 [=====] - 6s 95us/step - loss: 0.4515 - acc: 0.8809 - val_loss: 0.1770 - val_acc: 0.9544

Epoch 4/22

60000/60000 [=====] - 6s 93us/step - loss: 0.3605 - acc: 0.9086 - val_loss: 0.1603 - val_acc: 0.9598

Epoch 5/22

60000/60000 [=====] - 5s 91us/step - loss: 0.3098 - acc: 0.9238 - val_loss: 0.1407 - val_acc: 0.9652

Epoch 6/22

60000/60000 [=====] - 6s 93us/step - loss: 0.2733 - acc: 0.9344 - val_loss: 0.1306 - val_acc: 0.9678

Epoch 7/22

60000/60000 [=====] - 6s 95us/step - loss: 0.2510 - acc: 0.9403 - val_loss: 0.1234 - val_acc: 0.9706

Epoch 8/22

60000/60000 [=====] - 6s 92us/step - loss: 0.2338 - acc: 0.9445 - val_loss: 0.1102 - val_acc: 0.9721

Epoch 9/22

60000/60000 [=====] - 5s 91us/step - loss: 0.2155 - acc: 0.9492 - val_loss: 0.1160 - val_acc: 0.9721

Epoch 10/22

60000/60000 [=====] - 6s 93us/step - loss: 0.2071 - acc: 0.9517 - val_loss: 0.1066 - val_acc: 0.9742

Epoch 11/22

60000/60000 [=====] - 6s 94us/step - loss: 0.1990 - acc: 0.9537 - val_loss: 0.0999 - val_acc: 0.9749

Epoch 12/22

60000/60000 [=====] - 6s 92us/step - loss: 0.1885 - acc: 0.9569 - val_loss: 0.1000 - val_acc: 0.9759

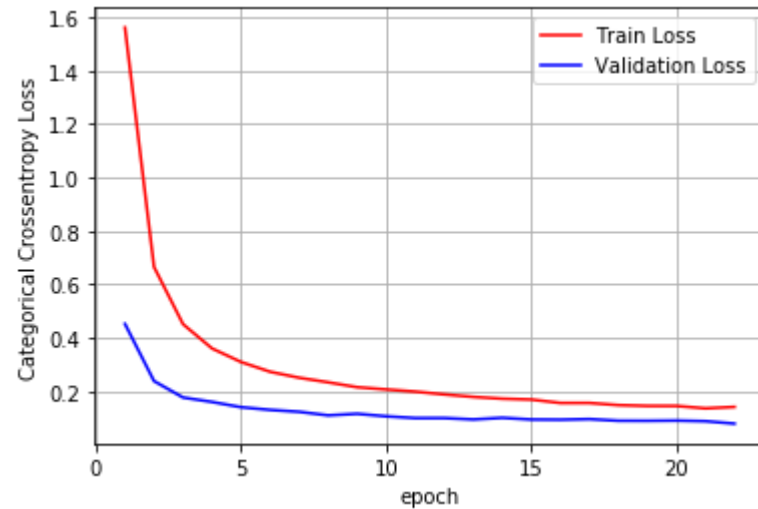
Epoch 13/22
60000/60000 [=====] - 6s 93us/step - loss: 0.1792 - acc: 0.9588 - val_loss: 0.0948 - val_acc: 0.9777
Epoch 14/22
60000/60000 [=====] - 6s 93us/step - loss: 0.1725 - acc: 0.9602 - val_loss: 0.1010 - val_acc: 0.9768
Epoch 15/22
60000/60000 [=====] - 5s 91us/step - loss: 0.1693 - acc: 0.9605 - val_loss: 0.0946 - val_acc: 0.9776
Epoch 16/22
60000/60000 [=====] - 6s 92us/step - loss: 0.1565 - acc: 0.9633 - val_loss: 0.0939 - val_acc: 0.9773
Epoch 17/22
60000/60000 [=====] - 6s 93us/step - loss: 0.1565 - acc: 0.9644 - val_loss: 0.0961 - val_acc: 0.9779
Epoch 18/22
60000/60000 [=====] - 6s 94us/step - loss: 0.1485 - acc: 0.9666 - val_loss: 0.0900 - val_acc: 0.9786
Epoch 19/22
60000/60000 [=====] - 6s 93us/step - loss: 0.1456 - acc: 0.9673 - val_loss: 0.0898 - val_acc: 0.9789
Epoch 20/22
60000/60000 [=====] - 6s 92us/step - loss: 0.1453 - acc: 0.9669 - val_loss: 0.0906 - val_acc: 0.9798
Epoch 21/22
60000/60000 [=====] - 6s 95us/step - loss: 0.1363 - acc: 0.9686 - val_loss: 0.0883 - val_acc: 0.9808
Epoch 22/22
60000/60000 [=====] - 6s 93us/step - loss: 0.1417 - acc: 0.9680 - val_loss: 0.0792 - val_acc: 0.9828
CPU times: user 2min 41s, sys: 13 s, total: 2min 54s
Wall time: 2min 7s

In [59]:

```
1 score = model_relu.evaluate(X_test, Y_test, verbose=0)
2 print('Test score:', score[0])
3 print('Test accuracy:', score[1])
4
5 fig,ax = plt.subplots(1,1)
6 ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')
7
8 # list of epoch numbers
9 x = list(range(1,nb_epoch+1))
10
11 vy = history.history['val_loss']
12 ty = history.history['loss']
13 plt_dynamic(x, vy, ty, ax)
```

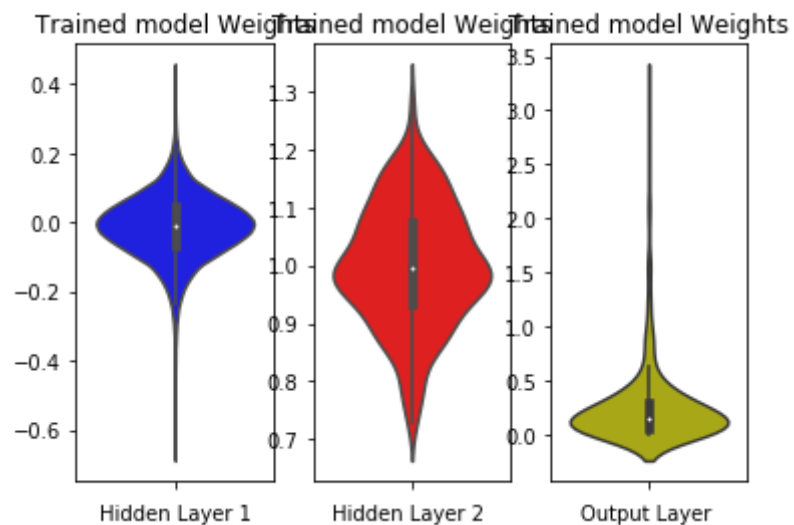
Test score: 0.07917401027954184

Test accuracy: 0.9828



In [60]:

```
1 %%time
2 w_after = model_relu.get_weights()
3
4 h1_w = w_after[0].flatten().reshape(-1,1)
5 h2_w = w_after[2].flatten().reshape(-1,1)
6 out_w = w_after[4].flatten().reshape(-1,1)
7
8 fig = plt.figure()
9 plt.title("Weight matrices after model trained")
10 plt.subplot(1, 3, 1)
11 plt.title("Trained model Weights")
12 ax = sns.violinplot(y=h1_w,color='b')
13 plt.xlabel('Hidden Layer 1')
14
15 plt.subplot(1, 3, 2)
16 plt.title("Trained model Weights")
17 ax = sns.violinplot(y=h2_w, color='r')
18 plt.xlabel('Hidden Layer 2 ')
19
20 plt.subplot(1, 3, 3)
21 plt.title("Trained model Weights")
22 ax = sns.violinplot(y=out_w,color='y')
23 plt.xlabel('Output Layer ')
24 plt.show()
```



2 hidden layer - MLP with Batch normalization and Dropout(0.25)

```
In [61]: 1 %%time
2 model_relu = Sequential()
3 model_relu.add(Dense(430, activation='relu', input_shape=(input_dim,), kernel_initializer=he_normal(seed=None)))
4 model_relu.add(BatchNormalization())
5 model_relu.add(Dropout(0.25))
6 model_relu.add(Dense(322, activation='relu', kernel_initializer=he_normal(seed=None)))
7 model_relu.add(BatchNormalization())
8 model_relu.add(Dropout(0.25))
9 model_relu.add(Dense(output_dim, activation='softmax'))
10
11 print(model_relu.summary())
12
13 model_relu.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
14
15 history = model_relu.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, validation_data=(X_test, Y_test))
```

Model: "sequential_13"

Layer (type)	Output Shape	Param #
dense_53 (Dense)	(None, 430)	337550
batch_normalization_41 (Batch Normalization)	(None, 430)	1720
dropout_41 (Dropout)	(None, 430)	0
dense_54 (Dense)	(None, 322)	138782
batch_normalization_42 (Batch Normalization)	(None, 322)	1288
dropout_42 (Dropout)	(None, 322)	0
dense_55 (Dense)	(None, 10)	3230

=====
Total params: 482,570
Trainable params: 481,066
Non-trainable params: 1,504

None

Train on 60000 samples, validate on 10000 samples

Epoch 1/22

60000/60000 [=====] - 6s 108us/step - loss: 0.2631 - acc: 0.9192 - val_loss: 0.1142 - val_acc: 0.9656

Epoch 2/22

60000/60000 [=====] - 4s 59us/step - loss: 0.1189 - acc: 0.9634 - val_loss: 0.0845 - val_acc: 0.9738

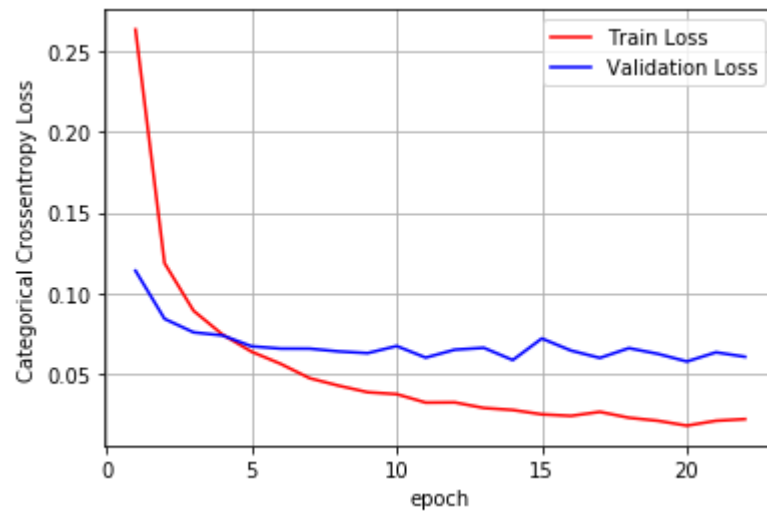
Epoch 3/22

```
60000/60000 [=====] - 3s 57us/step - loss: 0.0894 - acc: 0.9722 - val_loss: 0.0761 - val_acc: 0.9779
Epoch 4/22
60000/60000 [=====] - 3s 55us/step - loss: 0.0747 - acc: 0.9760 - val_loss: 0.0742 - val_acc: 0.9782
Epoch 5/22
60000/60000 [=====] - 3s 53us/step - loss: 0.0642 - acc: 0.9796 - val_loss: 0.0675 - val_acc: 0.9792
Epoch 6/22
60000/60000 [=====] - 3s 55us/step - loss: 0.0567 - acc: 0.9813 - val_loss: 0.0661 - val_acc: 0.9808
Epoch 7/22
60000/60000 [=====] - 3s 54us/step - loss: 0.0478 - acc: 0.9845 - val_loss: 0.0661 - val_acc: 0.9808
Epoch 8/22
60000/60000 [=====] - 3s 55us/step - loss: 0.0432 - acc: 0.9859 - val_loss: 0.0643 - val_acc: 0.9803
Epoch 9/22
60000/60000 [=====] - 3s 55us/step - loss: 0.0392 - acc: 0.9867 - val_loss: 0.0633 - val_acc: 0.9816
Epoch 10/22
60000/60000 [=====] - 3s 57us/step - loss: 0.0380 - acc: 0.9871 - val_loss: 0.0677 - val_acc: 0.9821
Epoch 11/22
60000/60000 [=====] - 3s 57us/step - loss: 0.0328 - acc: 0.9889 - val_loss: 0.0605 - val_acc: 0.9847
Epoch 12/22
60000/60000 [=====] - 3s 57us/step - loss: 0.0329 - acc: 0.9891 - val_loss: 0.0654 - val_acc: 0.9829
Epoch 13/22
60000/60000 [=====] - 3s 57us/step - loss: 0.0294 - acc: 0.9899 - val_loss: 0.0666 - val_acc: 0.9817
Epoch 14/22
60000/60000 [=====] - 3s 55us/step - loss: 0.0282 - acc: 0.9903 - val_loss: 0.0590 - val_acc: 0.9839
Epoch 15/22
60000/60000 [=====] - 3s 57us/step - loss: 0.0255 - acc: 0.9911 - val_loss: 0.0723 - val_acc: 0.9812
Epoch 16/22
60000/60000 [=====] - 3s 55us/step - loss: 0.0246 - acc: 0.9916 - val_loss: 0.0649 - val_acc: 0.9831
Epoch 17/22
60000/60000 [=====] - 3s 57us/step - loss: 0.0270 - acc: 0.9908 - val_loss: 0.0603 - val_acc: 0.9828
Epoch 18/22
60000/60000 [=====] - 3s 54us/step - loss: 0.0234 - acc: 0.9922 - val_loss: 0.0664 - val_acc: 0.9819
Epoch 19/22
60000/60000 [=====] - 3s 56us/step - loss: 0.0215 - acc: 0.9928 - val_loss: 0.0628 - val_acc: 0.9829
Epoch 20/22
60000/60000 [=====] - 3s 58us/step - loss: 0.0185 - acc: 0.9932 - val_loss: 0.0581 - val_acc: 0.9845
Epoch 21/22
60000/60000 [=====] - 3s 54us/step - loss: 0.0215 - acc: 0.9928 - val_loss: 0.0638 - val_acc: 0.9846
Epoch 22/22
60000/60000 [=====] - 3s 55us/step - loss: 0.0226 - acc: 0.9922 - val_loss: 0.0610 - val_acc: 0.9838
CPU times: user 1min 35s, sys: 7.73 s, total: 1min 43s
Wall time: 1min 17s
```

```
In [62]: 1 score = model_relu.evaluate(X_test, Y_test, verbose=0)
2 print('Test score:', score[0])
3 print('Test accuracy:', score[1])
4 fig,ax = plt.subplots(1,1)
5 ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')
6
7 # list of epoch numbers
8 x = list(range(1,nb_epoch+1))
9
10 vy = history.history['val_loss']
11 ty = history.history['loss']
12 plt_dynamic(x, vy, ty, ax)
```

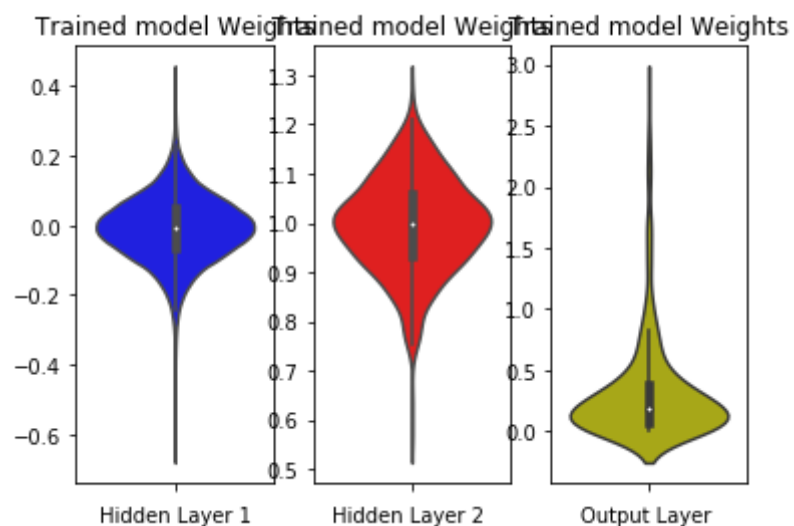
Test score: 0.06104755468893745

Test accuracy: 0.9838



In [63]:

```
1 %%time
2 w_after = model_relu.get_weights()
3
4 h1_w = w_after[0].flatten().reshape(-1,1)
5 h2_w = w_after[2].flatten().reshape(-1,1)
6 out_w = w_after[4].flatten().reshape(-1,1)
7
8 fig = plt.figure()
9 plt.title("Weight matrices after model trained")
10 plt.subplot(1, 3, 1)
11 plt.title("Trained model Weights")
12 ax = sns.violinplot(y=h1_w,color='b')
13 plt.xlabel('Hidden Layer 1')
14
15 plt.subplot(1, 3, 2)
16 plt.title("Trained model Weights")
17 ax = sns.violinplot(y=h2_w, color='r')
18 plt.xlabel('Hidden Layer 2 ')
19
20 plt.subplot(1, 3, 3)
21 plt.title("Trained model Weights")
22 ax = sns.violinplot(y=out_w,color='y')
23 plt.xlabel('Output Layer ')
24 plt.show()
```



3 hidden layer - MLP with Batch normalization and Dropout(0.25)

In [64]:

```
1 %%time
2 model_relu = Sequential()
3 model_relu.add(Dense(320, activation='relu', input_shape=(input_dim,), kernel_initializer=he_normal(seed=None)))
4 model_relu.add(BatchNormalization())
5 model_relu.add(Dropout(0.25))
6 model_relu.add(Dense(270, activation='relu', kernel_initializer=he_normal(seed=None)) )
7 model_relu.add(BatchNormalization())
8 model_relu.add(Dropout(0.25))
9 model_relu.add(Dense(162, activation='relu', input_shape=(input_dim,), kernel_initializer=he_normal(seed=None)))
10 model_relu.add(BatchNormalization())
11 model_relu.add(Dropout(0.25))
12 model_relu.add(Dense(output_dim, activation='softmax'))
13
14 print(model_relu.summary())
15
16 model_relu.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
17
18 history = model_relu.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, validation_data=(X_test, Y_test))
```

Model: "sequential_14"

Layer (type)	Output Shape	Param #
=====		
dense_56 (Dense)	(None, 320)	251200
batch_normalization_43 (Batch Normalization)	(None, 320)	1280
dropout_43 (Dropout)	(None, 320)	0
dense_57 (Dense)	(None, 270)	86670
batch_normalization_44 (Batch Normalization)	(None, 270)	1080
dropout_44 (Dropout)	(None, 270)	0
dense_58 (Dense)	(None, 162)	43902
batch_normalization_45 (Batch Normalization)	(None, 162)	648
dropout_45 (Dropout)	(None, 162)	0
dense_59 (Dense)	(None, 10)	1630
=====		
Total params: 386,410		
Trainable params: 384,906		

Non-trainable params: 1,504

None

Train on 60000 samples, validate on 10000 samples

Epoch 1/22

60000/60000 [=====] - 7s 123us/step - loss: 0.3332 - acc: 0.8979 - val_loss: 0.1211 - val_acc: 0.9635

Epoch 2/22

60000/60000 [=====] - 4s 69us/step - loss: 0.1476 - acc: 0.9552 - val_loss: 0.0920 - val_acc: 0.9712

Epoch 3/22

60000/60000 [=====] - 4s 72us/step - loss: 0.1152 - acc: 0.9647 - val_loss: 0.0842 - val_acc: 0.9732

Epoch 4/22

60000/60000 [=====] - 4s 70us/step - loss: 0.0954 - acc: 0.9700 - val_loss: 0.0704 - val_acc: 0.9777

Epoch 5/22

60000/60000 [=====] - 4s 68us/step - loss: 0.0809 - acc: 0.9744 - val_loss: 0.0716 - val_acc: 0.9786

Epoch 6/22

60000/60000 [=====] - 4s 70us/step - loss: 0.0708 - acc: 0.9769 - val_loss: 0.0657 - val_acc: 0.9790

Epoch 7/22

60000/60000 [=====] - 4s 72us/step - loss: 0.0665 - acc: 0.9784 - val_loss: 0.0660 - val_acc: 0.9802

Epoch 8/22

60000/60000 [=====] - 4s 67us/step - loss: 0.0598 - acc: 0.9805 - val_loss: 0.0615 - val_acc: 0.9805

Epoch 9/22

60000/60000 [=====] - 4s 67us/step - loss: 0.0561 - acc: 0.9819 - val_loss: 0.0637 - val_acc: 0.9798

Epoch 10/22

60000/60000 [=====] - 4s 69us/step - loss: 0.0523 - acc: 0.9826 - val_loss: 0.0670 - val_acc: 0.9806

Epoch 11/22

60000/60000 [=====] - 4s 68us/step - loss: 0.0480 - acc: 0.9847 - val_loss: 0.0637 - val_acc: 0.9819

Epoch 12/22

60000/60000 [=====] - 4s 68us/step - loss: 0.0437 - acc: 0.9859 - val_loss: 0.0608 - val_acc: 0.9824

Epoch 13/22

60000/60000 [=====] - 4s 67us/step - loss: 0.0428 - acc: 0.9863 - val_loss: 0.0608 - val_acc: 0.9836

Epoch 14/22

60000/60000 [=====] - 4s 67us/step - loss: 0.0425 - acc: 0.9862 - val_loss: 0.0617 - val_acc: 0.9818

Epoch 15/22

60000/60000 [=====] - 4s 68us/step - loss: 0.0379 - acc: 0.9874 - val_loss: 0.0643 - val_acc: 0.9822

Epoch 16/22

60000/60000 [=====] - 4s 67us/step - loss: 0.0359 - acc: 0.9883 - val_loss: 0.0690 - val_acc: 0.9809

Epoch 17/22

60000/60000 [=====] - 4s 70us/step - loss: 0.0363 - acc: 0.9878 - val_loss: 0.0632 - val_acc: 0.9831

Epoch 18/22

60000/60000 [=====] - 4s 66us/step - loss: 0.0320 - acc: 0.9893 - val_loss: 0.0596 - val_acc: 0.9828

Epoch 19/22

60000/60000 [=====] - 4s 70us/step - loss: 0.0316 - acc: 0.9893 - val_loss: 0.0570 - val_acc: 0.9839

Epoch 20/22

60000/60000 [=====] - 4s 68us/step - loss: 0.0310 - acc: 0.9899 - val_loss: 0.0565 - val_acc: 0.9841

Epoch 21/22

60000/60000 [=====] - 4s 67us/step - loss: 0.0290 - acc: 0.9901 - val_loss: 0.0604 - val_acc: 0.9837

Epoch 22/22

60000/60000 [=====] - 4s 70us/step - loss: 0.0255 - acc: 0.9913 - val_loss: 0.0632 - val_acc: 0.9823

CPU times: user 2min, sys: 9.8 s, total: 2min 9s

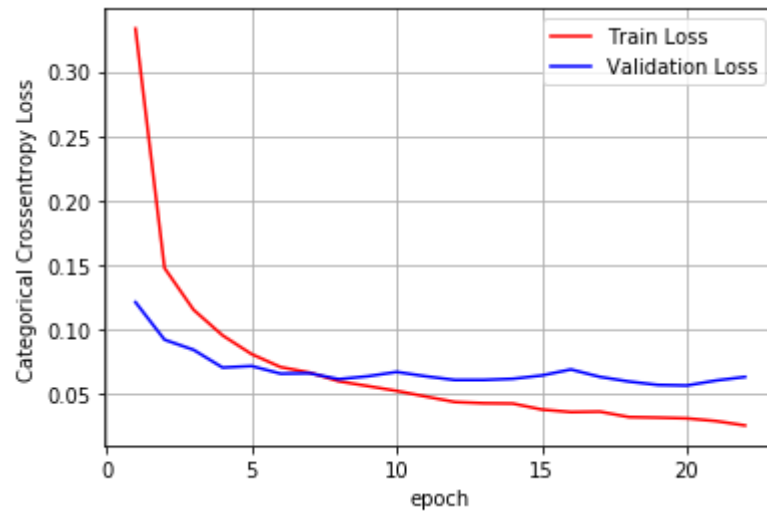
Wall time: 1min 34s

In [65]:

```
1 score = model_relu.evaluate(X_test, Y_test, verbose=0)
2 print('Test score:', score[0])
3 print('Test accuracy:', score[1])
4
5 fig,ax = plt.subplots(1,1)
6 ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')
7
8 # List of epoch numbers
9 x = list(range(1,nb_epoch+1))
10
11 vy = history.history['val_loss']
12 ty = history.history['loss']
13 plt_dynamic(x, vy, ty, ax)
```

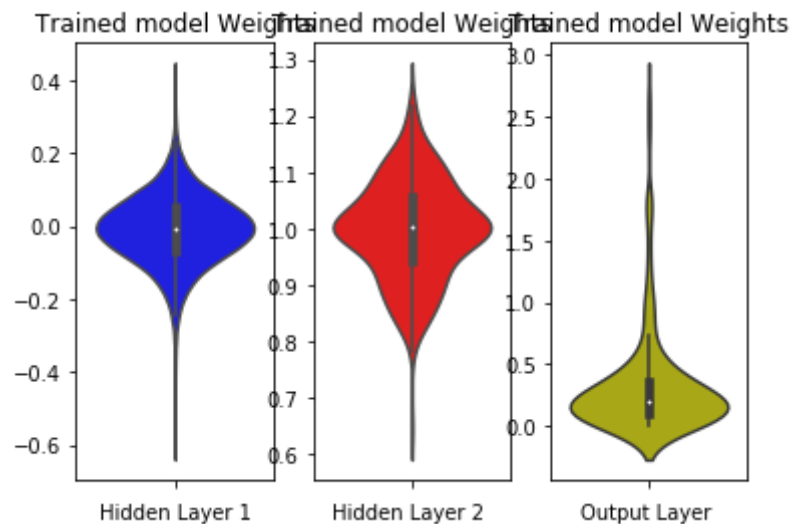
Test score: 0.06317311227827886

Test accuracy: 0.9823



In [66]:

```
1 %%time
2 w_after = model_relu.get_weights()
3
4 h1_w = w_after[0].flatten().reshape(-1,1)
5 h2_w = w_after[2].flatten().reshape(-1,1)
6 out_w = w_after[4].flatten().reshape(-1,1)
7
8 fig = plt.figure()
9 plt.title("Weight matrices after model trained")
10 plt.subplot(1, 3, 1)
11 plt.title("Trained model Weights")
12 ax = sns.violinplot(y=h1_w,color='b')
13 plt.xlabel('Hidden Layer 1')
14
15 plt.subplot(1, 3, 2)
16 plt.title("Trained model Weights")
17 ax = sns.violinplot(y=h2_w, color='r')
18 plt.xlabel('Hidden Layer 2 ')
19
20 plt.subplot(1, 3, 3)
21 plt.title("Trained model Weights")
22 ax = sns.violinplot(y=out_w,color='y')
23 plt.xlabel('Output Layer ')
24 plt.show()
```



5 hidden layer - MLP with Batch normalization and Dropout(0.25)

In [67]:

```
1 %%time
2 model_relu = Sequential()
3 model_relu.add(Dense(340, activation='relu', input_shape=(input_dim,), kernel_initializer=he_normal(seed=None)))
4 model_relu.add(BatchNormalization())
5 model_relu.add(Dropout(0.25))
6 model_relu.add(Dense(190, activation='relu', kernel_initializer=he_normal(seed=None)) )
7 model_relu.add(BatchNormalization())
8 model_relu.add(Dropout(0.25))
9 model_relu.add(Dense(112, activation='relu', kernel_initializer=he_normal(seed=None)))
10 model_relu.add(BatchNormalization())
11 model_relu.add(Dropout(0.25))
12 model_relu.add(Dense(72, activation='relu', kernel_initializer=he_normal(seed=None)))
13 model_relu.add(BatchNormalization())
14 model_relu.add(Dropout(0.25))
15 model_relu.add(Dense(38, activation='relu', kernel_initializer=he_normal(seed=None)))
16 model_relu.add(BatchNormalization())
17 model_relu.add(Dropout(0.25))
18 model_relu.add(Dense(output_dim, activation='softmax'))
19
20 print(model_relu.summary())
21
22 model_relu.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
23
24 history = model_relu.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, validation_data=(X_test, Y_test))
```

Model: "sequential_15"

Layer (type)	Output Shape	Param #
=====		
dense_60 (Dense)	(None, 340)	266900
batch_normalization_46 (Batch Normalization)	(None, 340)	1360
dropout_46 (Dropout)	(None, 340)	0
dense_61 (Dense)	(None, 190)	64790
batch_normalization_47 (Batch Normalization)	(None, 190)	760
dropout_47 (Dropout)	(None, 190)	0
dense_62 (Dense)	(None, 112)	21392
batch_normalization_48 (Batch Normalization)	(None, 112)	448

dropout_48 (Dropout)	(None, 112)	0
dense_63 (Dense)	(None, 72)	8136
batch_normalization_49 (Batch Normalization)	(None, 72)	288
dropout_49 (Dropout)	(None, 72)	0
dense_64 (Dense)	(None, 38)	2774
batch_normalization_50 (Batch Normalization)	(None, 38)	152
dropout_50 (Dropout)	(None, 38)	0
dense_65 (Dense)	(None, 10)	390

=====
Total params: 367,390
Trainable params: 365,886
Non-trainable params: 1,504

None

Train on 60000 samples, validate on 10000 samples

Epoch 1/22

60000/60000 [=====] - 9s 158us/step - loss: 0.6399 - acc: 0.8115 - val_loss: 0.1626 - val_acc: 0.9524

Epoch 2/22

60000/60000 [=====] - 5s 90us/step - loss: 0.2371 - acc: 0.9354 - val_loss: 0.1139 - val_acc: 0.9656

Epoch 3/22

60000/60000 [=====] - 5s 91us/step - loss: 0.1787 - acc: 0.9519 - val_loss: 0.1129 - val_acc: 0.9670

Epoch 4/22

60000/60000 [=====] - 6s 92us/step - loss: 0.1463 - acc: 0.9602 - val_loss: 0.0871 - val_acc: 0.9752

Epoch 5/22

60000/60000 [=====] - 6s 93us/step - loss: 0.1288 - acc: 0.9641 - val_loss: 0.0904 - val_acc: 0.9751

Epoch 6/22

60000/60000 [=====] - 6s 93us/step - loss: 0.1159 - acc: 0.9678 - val_loss: 0.0823 - val_acc: 0.9773

Epoch 7/22

60000/60000 [=====] - 6s 93us/step - loss: 0.1024 - acc: 0.9720 - val_loss: 0.0843 - val_acc: 0.9769

Epoch 8/22

60000/60000 [=====] - 6s 94us/step - loss: 0.0970 - acc: 0.9727 - val_loss: 0.0812 - val_acc: 0.9780

Epoch 9/22

60000/60000 [=====] - 6s 96us/step - loss: 0.0920 - acc: 0.9744 - val_loss: 0.0740 - val_acc: 0.9801

Epoch 10/22

60000/60000 [=====] - 6s 92us/step - loss: 0.0849 - acc: 0.9762 - val_loss: 0.0728 - val_acc: 0.9798

Epoch 11/22

60000/60000 [=====] - 6s 93us/step - loss: 0.0778 - acc: 0.9781 - val_loss: 0.0756 - val_acc: 0.9801

Epoch 12/22

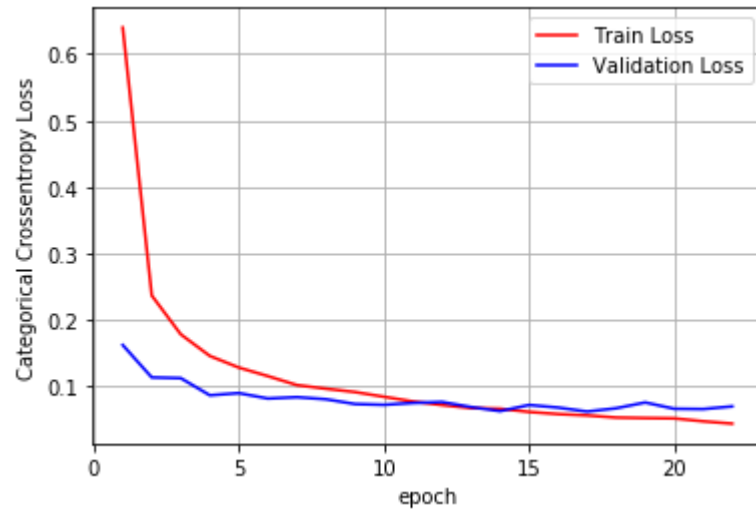
60000/60000 [=====] - 5s 91us/step - loss: 0.0724 - acc: 0.9793 - val_loss: 0.0770 - val_acc: 0.9799

Epoch 13/22
60000/60000 [=====] - 5s 90us/step - loss: 0.0678 - acc: 0.9810 - val_loss: 0.0694 - val_acc: 0.9820
Epoch 14/22
60000/60000 [=====] - 6s 92us/step - loss: 0.0669 - acc: 0.9815 - val_loss: 0.0633 - val_acc: 0.9827
Epoch 15/22
60000/60000 [=====] - 5s 92us/step - loss: 0.0621 - acc: 0.9828 - val_loss: 0.0725 - val_acc: 0.9822
Epoch 16/22
60000/60000 [=====] - 5s 90us/step - loss: 0.0589 - acc: 0.9833 - val_loss: 0.0686 - val_acc: 0.9823
Epoch 17/22
60000/60000 [=====] - 6s 94us/step - loss: 0.0569 - acc: 0.9838 - val_loss: 0.0626 - val_acc: 0.9828
Epoch 18/22
60000/60000 [=====] - 6s 92us/step - loss: 0.0536 - acc: 0.9852 - val_loss: 0.0676 - val_acc: 0.9825
Epoch 19/22
60000/60000 [=====] - 6s 92us/step - loss: 0.0529 - acc: 0.9847 - val_loss: 0.0763 - val_acc: 0.9805
Epoch 20/22
60000/60000 [=====] - 6s 95us/step - loss: 0.0524 - acc: 0.9849 - val_loss: 0.0668 - val_acc: 0.9833
Epoch 21/22
60000/60000 [=====] - 6s 92us/step - loss: 0.0480 - acc: 0.9864 - val_loss: 0.0664 - val_acc: 0.9841
Epoch 22/22
60000/60000 [=====] - 6s 92us/step - loss: 0.0445 - acc: 0.9867 - val_loss: 0.0704 - val_acc: 0.9838
CPU times: user 2min 40s, sys: 13 s, total: 2min 53s
Wall time: 2min 7s

```
In [68]: 1 score = model_relu.evaluate(X_test, Y_test, verbose=0)
2 print('Test score:', score[0])
3 print('Test accuracy:', score[1])
4
5 fig,ax = plt.subplots(1,1)
6 ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')
7
8 # list of epoch numbers
9 x = list(range(1,nb_epoch+1))
10
11 vy = history.history['val_loss']
12 ty = history.history['loss']
13 plt_dynamic(x, vy, ty, ax)
```

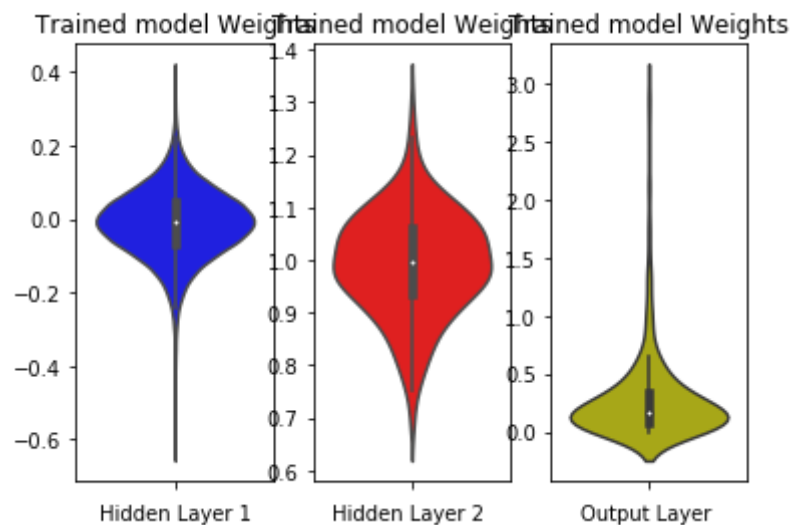
Test score: 0.07041437144926749

Test accuracy: 0.9838



In [69]:

```
1 %%time
2 w_after = model_relu.get_weights()
3
4 h1_w = w_after[0].flatten().reshape(-1,1)
5 h2_w = w_after[2].flatten().reshape(-1,1)
6 out_w = w_after[4].flatten().reshape(-1,1)
7
8 fig = plt.figure()
9 plt.title("Weight matrices after model trained")
10 plt.subplot(1, 3, 1)
11 plt.title("Trained model Weights")
12 ax = sns.violinplot(y=h1_w,color='b')
13 plt.xlabel('Hidden Layer 1')
14
15 plt.subplot(1, 3, 2)
16 plt.title("Trained model Weights")
17 ax = sns.violinplot(y=h2_w, color='r')
18 plt.xlabel('Hidden Layer 2 ')
19
20 plt.subplot(1, 3, 3)
21 plt.title("Trained model Weights")
22 ax = sns.violinplot(y=out_w,color='y')
23 plt.xlabel('Output Layer ')
24 plt.show()
```



2 hidden layer - MLP with Batch normalization,Dropout(0.5) and Mean Squared Error

```
In [70]: 1 %%time
2 model_relu = Sequential()
3 model_relu.add(Dense(430, activation='relu', input_shape=(input_dim,), kernel_initializer=he_normal(seed=None)))
4 model_relu.add(BatchNormalization())
5 model_relu.add(Dropout(0.5))
6 model_relu.add(Dense(322, activation='relu', kernel_initializer=he_normal(seed=None)))
7 model_relu.add(BatchNormalization())
8 model_relu.add(Dropout(0.5))
9 model_relu.add(Dense(output_dim, activation='softmax'))
10
11 print(model_relu.summary())
12
13 model_relu.compile(optimizer='adam', loss='mean_squared_error', metrics=['accuracy'])
14
15 history = model_relu.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, validation_data=(X_test, Y_test))
```

Model: "sequential_16"

Layer (type)	Output Shape	Param #
=====		
dense_66 (Dense)	(None, 430)	337550
batch_normalization_51 (Batch Normalization)	(None, 430)	1720
dropout_51 (Dropout)	(None, 430)	0
dense_67 (Dense)	(None, 322)	138782
batch_normalization_52 (Batch Normalization)	(None, 322)	1288
dropout_52 (Dropout)	(None, 322)	0
dense_68 (Dense)	(None, 10)	3230
=====		
Total params: 482,570		
Trainable params: 481,066		
Non-trainable params: 1,504		

None

Train on 60000 samples, validate on 10000 samples

Epoch 1/22

60000/60000 [=====] - 7s 120us/step - loss: 0.0200 - acc: 0.8633 - val_loss: 0.0079 - val_acc: 0.9483

Epoch 2/22

60000/60000 [=====] - 3s 55us/step - loss: 0.0103 - acc: 0.9329 - val_loss: 0.0060 - val_acc: 0.9611

Epoch 3/22

```

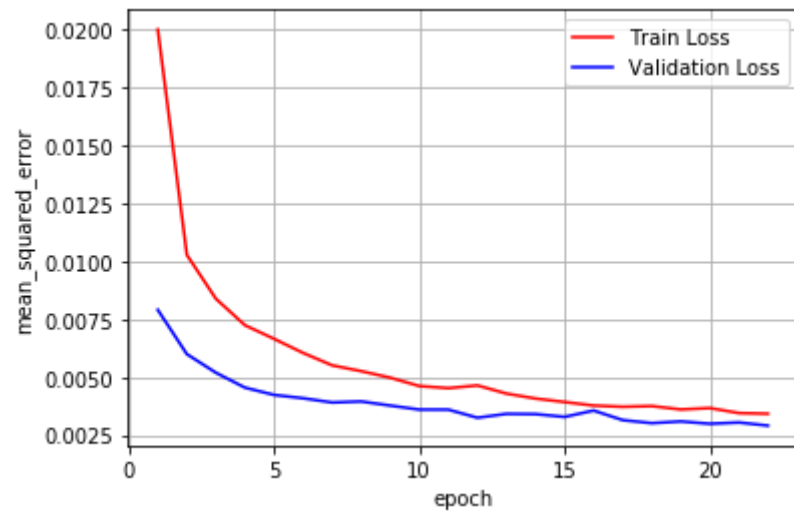
60000/60000 [=====] - 3s 54us/step - loss: 0.0084 - acc: 0.9455 - val_loss: 0.0052 - val_acc: 0.9666
Epoch 4/22
60000/60000 [=====] - 3s 56us/step - loss: 0.0072 - acc: 0.9534 - val_loss: 0.0045 - val_acc: 0.9705
Epoch 5/22
60000/60000 [=====] - 3s 56us/step - loss: 0.0067 - acc: 0.9568 - val_loss: 0.0042 - val_acc: 0.9730
Epoch 6/22
60000/60000 [=====] - 3s 55us/step - loss: 0.0060 - acc: 0.9612 - val_loss: 0.0041 - val_acc: 0.9733
Epoch 7/22
60000/60000 [=====] - 4s 58us/step - loss: 0.0055 - acc: 0.9649 - val_loss: 0.0039 - val_acc: 0.9749
Epoch 8/22
60000/60000 [=====] - 3s 58us/step - loss: 0.0053 - acc: 0.9664 - val_loss: 0.0039 - val_acc: 0.9743
Epoch 9/22
60000/60000 [=====] - 3s 55us/step - loss: 0.0050 - acc: 0.9684 - val_loss: 0.0038 - val_acc: 0.9759
Epoch 10/22
60000/60000 [=====] - 3s 55us/step - loss: 0.0046 - acc: 0.9704 - val_loss: 0.0036 - val_acc: 0.9759
Epoch 11/22
60000/60000 [=====] - 3s 55us/step - loss: 0.0045 - acc: 0.9710 - val_loss: 0.0036 - val_acc: 0.9771
Epoch 12/22
60000/60000 [=====] - 4s 59us/step - loss: 0.0046 - acc: 0.9699 - val_loss: 0.0032 - val_acc: 0.9792
Epoch 13/22
60000/60000 [=====] - 3s 57us/step - loss: 0.0043 - acc: 0.9723 - val_loss: 0.0034 - val_acc: 0.9780
Epoch 14/22
60000/60000 [=====] - 3s 54us/step - loss: 0.0041 - acc: 0.9736 - val_loss: 0.0034 - val_acc: 0.9780
Epoch 15/22
60000/60000 [=====] - 3s 55us/step - loss: 0.0039 - acc: 0.9750 - val_loss: 0.0033 - val_acc: 0.9782
Epoch 16/22
60000/60000 [=====] - 3s 55us/step - loss: 0.0038 - acc: 0.9759 - val_loss: 0.0036 - val_acc: 0.9771
Epoch 17/22
60000/60000 [=====] - 3s 55us/step - loss: 0.0037 - acc: 0.9764 - val_loss: 0.0031 - val_acc: 0.9798
Epoch 18/22
60000/60000 [=====] - 3s 55us/step - loss: 0.0038 - acc: 0.9762 - val_loss: 0.0030 - val_acc: 0.9808
Epoch 19/22
60000/60000 [=====] - 3s 53us/step - loss: 0.0036 - acc: 0.9770 - val_loss: 0.0031 - val_acc: 0.9801
Epoch 20/22
60000/60000 [=====] - 3s 54us/step - loss: 0.0037 - acc: 0.9768 - val_loss: 0.0030 - val_acc: 0.9811
Epoch 21/22
60000/60000 [=====] - 3s 57us/step - loss: 0.0034 - acc: 0.9783 - val_loss: 0.0030 - val_acc: 0.9813
Epoch 22/22
60000/60000 [=====] - 3s 55us/step - loss: 0.0034 - acc: 0.9781 - val_loss: 0.0029 - val_acc: 0.9819
CPU times: user 1min 35s, sys: 8.25 s, total: 1min 44s
Wall time: 1min 18s

```

```
In [71]: 1 score = model_relu.evaluate(X_test, Y_test, verbose=0)
2 print('Test score:', score[0])
3 print('Test accuracy:', score[1])
4 fig,ax = plt.subplots(1,1)
5 ax.set_xlabel('epoch') ; ax.set_ylabel('mean_squared_error')
6
7 # list of epoch numbers
8 x = list(range(1,nb_epoch+1))
9
10 vy = history.history['val_loss']
11 ty = history.history['loss']
12 plt_dynamic(x, vy, ty, ax)
```

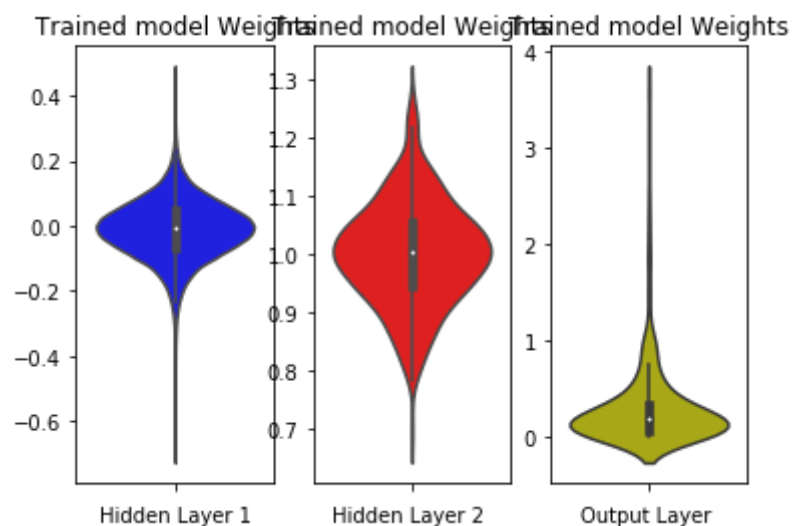
Test score: 0.002905523286913556

Test accuracy: 0.9819



In [72]:

```
1 %%time
2 w_after = model_relu.get_weights()
3
4 h1_w = w_after[0].flatten().reshape(-1,1)
5 h2_w = w_after[2].flatten().reshape(-1,1)
6 out_w = w_after[4].flatten().reshape(-1,1)
7
8 fig = plt.figure()
9 plt.title("Weight matrices after model trained")
10 plt.subplot(1, 3, 1)
11 plt.title("Trained model Weights")
12 ax = sns.violinplot(y=h1_w,color='b')
13 plt.xlabel('Hidden Layer 1')
14
15 plt.subplot(1, 3, 2)
16 plt.title("Trained model Weights")
17 ax = sns.violinplot(y=h2_w, color='r')
18 plt.xlabel('Hidden Layer 2 ')
19
20 plt.subplot(1, 3, 3)
21 plt.title("Trained model Weights")
22 ax = sns.violinplot(y=out_w,color='y')
23 plt.xlabel('Output Layer ')
24 plt.show()
```



3 hidden layer - MLP with Batch normalization,Dropout(0.5) and Mean Squared Error

In [73]:

```
1 %%time
2 model_relu = Sequential()
3 model_relu.add(Dense(320, activation='relu', input_shape=(input_dim,), kernel_initializer=he_normal(seed=None)))
4 model_relu.add(BatchNormalization())
5 model_relu.add(Dropout(0.5))
6 model_relu.add(Dense(270, activation='relu', kernel_initializer=he_normal(seed=None)) )
7 model_relu.add(BatchNormalization())
8 model_relu.add(Dropout(0.5))
9 model_relu.add(Dense(162, activation='relu', input_shape=(input_dim,), kernel_initializer=he_normal(seed=None)))
10 model_relu.add(BatchNormalization())
11 model_relu.add(Dropout(0.5))
12 model_relu.add(Dense(output_dim, activation='softmax'))
13
14 print(model_relu.summary())
15
16 model_relu.compile(optimizer='adam', loss='mean_squared_error', metrics=['accuracy'])
17
18 history = model_relu.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, validation_data=(X_test, Y_test))
```

Model: "sequential_17"

Layer (type)	Output Shape	Param #
=====		
dense_69 (Dense)	(None, 320)	251200
batch_normalization_53 (Batch Normalization)	(None, 320)	1280
dropout_53 (Dropout)	(None, 320)	0
dense_70 (Dense)	(None, 270)	86670
batch_normalization_54 (Batch Normalization)	(None, 270)	1080
dropout_54 (Dropout)	(None, 270)	0
dense_71 (Dense)	(None, 162)	43902
batch_normalization_55 (Batch Normalization)	(None, 162)	648
dropout_55 (Dropout)	(None, 162)	0
dense_72 (Dense)	(None, 10)	1630
=====		
Total params: 386,410		
Trainable params: 384,906		

Non-trainable params: 1,504

None

Train on 60000 samples, validate on 10000 samples

Epoch 1/22

60000/60000 [=====] - 8s 137us/step - loss: 0.0285 - acc: 0.7985 - val_loss: 0.0101 - val_acc: 0.9338

Epoch 2/22

60000/60000 [=====] - 4s 65us/step - loss: 0.0131 - acc: 0.9137 - val_loss: 0.0071 - val_acc: 0.9550

Epoch 3/22

60000/60000 [=====] - 4s 66us/step - loss: 0.0106 - acc: 0.9309 - val_loss: 0.0060 - val_acc: 0.9626

Epoch 4/22

60000/60000 [=====] - 4s 66us/step - loss: 0.0094 - acc: 0.9389 - val_loss: 0.0052 - val_acc: 0.9672

Epoch 5/22

60000/60000 [=====] - 4s 68us/step - loss: 0.0083 - acc: 0.9462 - val_loss: 0.0052 - val_acc: 0.9664

Epoch 6/22

60000/60000 [=====] - 4s 66us/step - loss: 0.0077 - acc: 0.9508 - val_loss: 0.0047 - val_acc: 0.9694

Epoch 7/22

60000/60000 [=====] - 4s 68us/step - loss: 0.0071 - acc: 0.9540 - val_loss: 0.0045 - val_acc: 0.9708

Epoch 8/22

60000/60000 [=====] - 4s 63us/step - loss: 0.0066 - acc: 0.9574 - val_loss: 0.0042 - val_acc: 0.9734

Epoch 9/22

60000/60000 [=====] - 4s 66us/step - loss: 0.0062 - acc: 0.9598 - val_loss: 0.0039 - val_acc: 0.9748

Epoch 10/22

60000/60000 [=====] - 4s 67us/step - loss: 0.0060 - acc: 0.9617 - val_loss: 0.0040 - val_acc: 0.9743

Epoch 11/22

60000/60000 [=====] - 4s 64us/step - loss: 0.0058 - acc: 0.9627 - val_loss: 0.0037 - val_acc: 0.9764

Epoch 12/22

60000/60000 [=====] - 4s 65us/step - loss: 0.0055 - acc: 0.9647 - val_loss: 0.0038 - val_acc: 0.9764

Epoch 13/22

60000/60000 [=====] - 4s 65us/step - loss: 0.0053 - acc: 0.9666 - val_loss: 0.0037 - val_acc: 0.9760

Epoch 14/22

60000/60000 [=====] - 4s 66us/step - loss: 0.0049 - acc: 0.9687 - val_loss: 0.0035 - val_acc: 0.9783

Epoch 15/22

60000/60000 [=====] - 4s 65us/step - loss: 0.0050 - acc: 0.9685 - val_loss: 0.0036 - val_acc: 0.9770

Epoch 16/22

60000/60000 [=====] - 4s 65us/step - loss: 0.0048 - acc: 0.9692 - val_loss: 0.0037 - val_acc: 0.9771

Epoch 17/22

60000/60000 [=====] - 4s 65us/step - loss: 0.0045 - acc: 0.9707 - val_loss: 0.0035 - val_acc: 0.9773

Epoch 18/22

60000/60000 [=====] - 4s 65us/step - loss: 0.0046 - acc: 0.9703 - val_loss: 0.0035 - val_acc: 0.9783

Epoch 19/22

60000/60000 [=====] - 4s 66us/step - loss: 0.0045 - acc: 0.9719 - val_loss: 0.0036 - val_acc: 0.9762

Epoch 20/22

60000/60000 [=====] - 4s 68us/step - loss: 0.0042 - acc: 0.9730 - val_loss: 0.0034 - val_acc: 0.9796

Epoch 21/22

60000/60000 [=====] - 4s 66us/step - loss: 0.0041 - acc: 0.9741 - val_loss: 0.0032 - val_acc: 0.9790

Epoch 22/22

60000/60000 [=====] - 4s 65us/step - loss: 0.0041 - acc: 0.9735 - val_loss: 0.0032 - val_acc: 0.9800

CPU times: user 1min 54s, sys: 8.76 s, total: 2min 3s

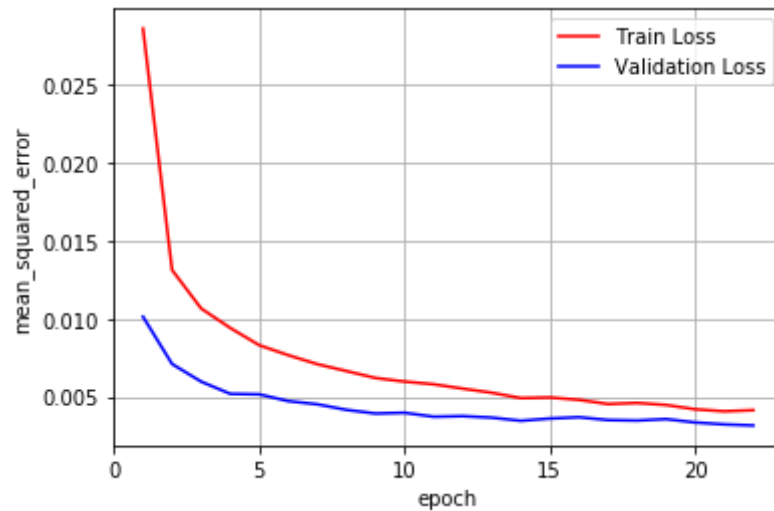
Wall time: 1min 32s

In [74]:

```
1 score = model_relu.evaluate(X_test, Y_test, verbose=0)
2 print('Test score:', score[0])
3 print('Test accuracy:', score[1])
4
5 fig,ax = plt.subplots(1,1)
6 ax.set_xlabel('epoch') ; ax.set_ylabel('mean_squared_error')
7
8 # List of epoch numbers
9 x = list(range(1,nb_epoch+1))
10
11 vy = history.history['val_loss']
12 ty = history.history['loss']
13 plt_dynamic(x, vy, ty, ax)
```

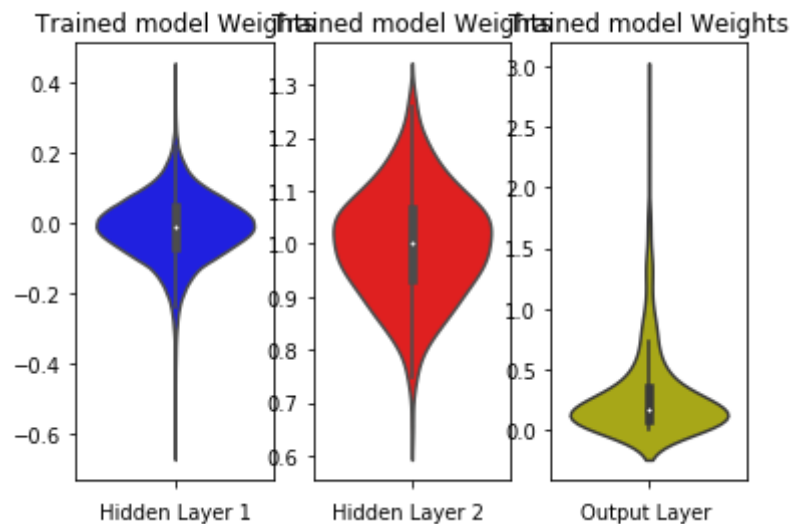
Test score: 0.0031677277905113464

Test accuracy: 0.98



In [75]:

```
1 %%time
2 w_after = model_relu.get_weights()
3
4 h1_w = w_after[0].flatten().reshape(-1,1)
5 h2_w = w_after[2].flatten().reshape(-1,1)
6 out_w = w_after[4].flatten().reshape(-1,1)
7
8 fig = plt.figure()
9 plt.title("Weight matrices after model trained")
10 plt.subplot(1, 3, 1)
11 plt.title("Trained model Weights")
12 ax = sns.violinplot(y=h1_w,color='b')
13 plt.xlabel('Hidden Layer 1')
14
15 plt.subplot(1, 3, 2)
16 plt.title("Trained model Weights")
17 ax = sns.violinplot(y=h2_w, color='r')
18 plt.xlabel('Hidden Layer 2 ')
19
20 plt.subplot(1, 3, 3)
21 plt.title("Trained model Weights")
22 ax = sns.violinplot(y=out_w,color='y')
23 plt.xlabel('Output Layer ')
24 plt.show()
```



5 hidden layer - MLP with Batch normalization,Dropout(0.5) and Mean Squared Error

In [76]:

```
1 %%time
2 model_relu = Sequential()
3 model_relu.add(Dense(340, activation='relu', input_shape=(input_dim,), kernel_initializer=he_normal(seed=None)))
4 model_relu.add(BatchNormalization())
5 model_relu.add(Dropout(0.5))
6 model_relu.add(Dense(190, activation='relu', kernel_initializer=he_normal(seed=None)) )
7 model_relu.add(BatchNormalization())
8 model_relu.add(Dropout(0.5))
9 model_relu.add(Dense(112, activation='relu', kernel_initializer=he_normal(seed=None)))
10 model_relu.add(BatchNormalization())
11 model_relu.add(Dropout(0.5))
12 model_relu.add(Dense(72, activation='relu', kernel_initializer=he_normal(seed=None)))
13 model_relu.add(BatchNormalization())
14 model_relu.add(Dropout(0.5))
15 model_relu.add(Dense(38, activation='relu', kernel_initializer=he_normal(seed=None)))
16 model_relu.add(BatchNormalization())
17 model_relu.add(Dropout(0.5))
18 model_relu.add(Dense(output_dim, activation='softmax'))
19
20 print(model_relu.summary())
21
22 model_relu.compile(optimizer='adam', loss='mean_squared_error', metrics=['accuracy'])
23
24 history = model_relu.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, validation_data=(X_test, Y_test))
```

Model: "sequential_18"

Layer (type)	Output Shape	Param #
=====		
dense_73 (Dense)	(None, 340)	266900
batch_normalization_56 (Batch Normalization)	(None, 340)	1360
dropout_56 (Dropout)	(None, 340)	0
dense_74 (Dense)	(None, 190)	64790
batch_normalization_57 (Batch Normalization)	(None, 190)	760
dropout_57 (Dropout)	(None, 190)	0
dense_75 (Dense)	(None, 112)	21392
batch_normalization_58 (Batch Normalization)	(None, 112)	448

dropout_58 (Dropout)	(None, 112)	0
dense_76 (Dense)	(None, 72)	8136
batch_normalization_59 (Batch Normalization)	(None, 72)	288
dropout_59 (Dropout)	(None, 72)	0
dense_77 (Dense)	(None, 38)	2774
batch_normalization_60 (Batch Normalization)	(None, 38)	152
dropout_60 (Dropout)	(None, 38)	0
dense_78 (Dense)	(None, 10)	390

=====
Total params: 367,390
Trainable params: 365,886
Non-trainable params: 1,504

None

Train on 60000 samples, validate on 10000 samples

Epoch 1/22

60000/60000 [=====] - 10s 171us/step - loss: 0.0692 - acc: 0.4424 - val_loss: 0.0222 - val_acc: 0.8628

Epoch 2/22

60000/60000 [=====] - 5s 89us/step - loss: 0.0287 - acc: 0.8108 - val_loss: 0.0099 - val_acc: 0.9366

Epoch 3/22

60000/60000 [=====] - 5s 91us/step - loss: 0.0177 - acc: 0.8909 - val_loss: 0.0081 - val_acc: 0.9509

Epoch 4/22

60000/60000 [=====] - 5s 91us/step - loss: 0.0142 - acc: 0.9137 - val_loss: 0.0075 - val_acc: 0.9533

Epoch 5/22

60000/60000 [=====] - 6s 94us/step - loss: 0.0124 - acc: 0.9252 - val_loss: 0.0065 - val_acc: 0.9617

Epoch 6/22

60000/60000 [=====] - 6s 93us/step - loss: 0.0115 - acc: 0.9311 - val_loss: 0.0063 - val_acc: 0.9633

Epoch 7/22

60000/60000 [=====] - 5s 90us/step - loss: 0.0104 - acc: 0.9376 - val_loss: 0.0066 - val_acc: 0.9621

Epoch 8/22

60000/60000 [=====] - 6s 93us/step - loss: 0.0098 - acc: 0.9415 - val_loss: 0.0059 - val_acc: 0.9661

Epoch 9/22

60000/60000 [=====] - 5s 91us/step - loss: 0.0095 - acc: 0.9434 - val_loss: 0.0057 - val_acc: 0.9671

Epoch 10/22

60000/60000 [=====] - 6s 92us/step - loss: 0.0091 - acc: 0.9448 - val_loss: 0.0054 - val_acc: 0.9683

Epoch 11/22

60000/60000 [=====] - 5s 90us/step - loss: 0.0087 - acc: 0.9480 - val_loss: 0.0056 - val_acc: 0.9672

Epoch 12/22

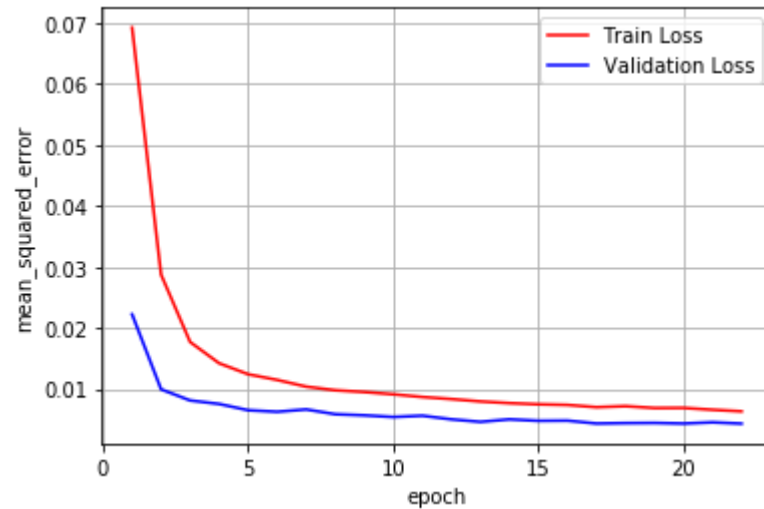
60000/60000 [=====] - 6s 92us/step - loss: 0.0083 - acc: 0.9506 - val_loss: 0.0050 - val_acc: 0.9713

Epoch 13/22
60000/60000 [=====] - 5s 91us/step - loss: 0.0079 - acc: 0.9530 - val_loss: 0.0046 - val_acc: 0.9738
Epoch 14/22
60000/60000 [=====] - 5s 90us/step - loss: 0.0077 - acc: 0.9547 - val_loss: 0.0050 - val_acc: 0.9706
Epoch 15/22
60000/60000 [=====] - 6s 92us/step - loss: 0.0075 - acc: 0.9560 - val_loss: 0.0048 - val_acc: 0.9733
Epoch 16/22
60000/60000 [=====] - 6s 95us/step - loss: 0.0074 - acc: 0.9558 - val_loss: 0.0048 - val_acc: 0.9724
Epoch 17/22
60000/60000 [=====] - 6s 92us/step - loss: 0.0070 - acc: 0.9581 - val_loss: 0.0043 - val_acc: 0.9752
Epoch 18/22
60000/60000 [=====] - 6s 92us/step - loss: 0.0072 - acc: 0.9569 - val_loss: 0.0044 - val_acc: 0.9749
Epoch 19/22
60000/60000 [=====] - 5s 92us/step - loss: 0.0069 - acc: 0.9593 - val_loss: 0.0044 - val_acc: 0.9744
Epoch 20/22
60000/60000 [=====] - 5s 91us/step - loss: 0.0069 - acc: 0.9590 - val_loss: 0.0043 - val_acc: 0.9749
Epoch 21/22
60000/60000 [=====] - 5s 90us/step - loss: 0.0066 - acc: 0.9609 - val_loss: 0.0045 - val_acc: 0.9737
Epoch 22/22
60000/60000 [=====] - 5s 91us/step - loss: 0.0063 - acc: 0.9624 - val_loss: 0.0043 - val_acc: 0.9756
CPU times: user 2min 39s, sys: 12.7 s, total: 2min 52s
Wall time: 2min 7s

```
In [77]: 1 score = model_relu.evaluate(X_test, Y_test, verbose=0)
2 print('Test score:', score[0])
3 print('Test accuracy:', score[1])
4
5 fig,ax = plt.subplots(1,1)
6 ax.set_xlabel('epoch') ; ax.set_ylabel('mean_squared_error')
7
8 # List of epoch numbers
9 x = list(range(1,nb_epoch+1))
10
11 vy = history.history['val_loss']
12 ty = history.history['loss']
13 plt_dynamic(x, vy, ty, ax)
```

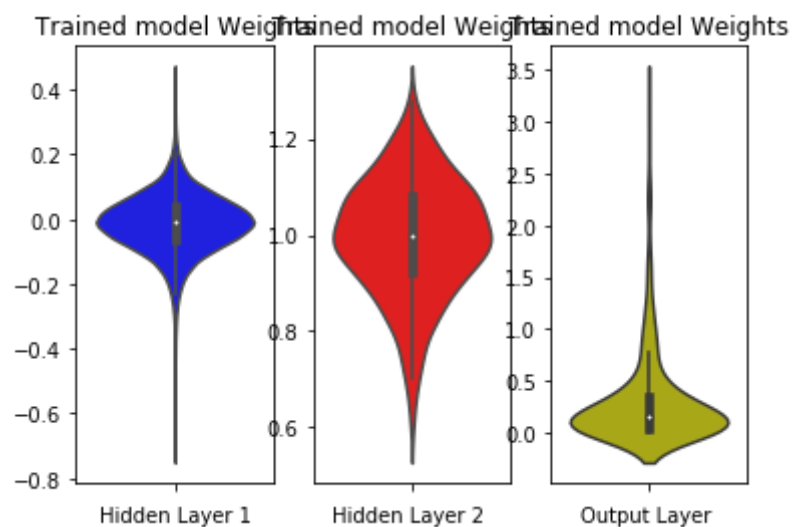
Test score: 0.004310477123901086

Test accuracy: 0.9756



In [78]:

```
1 %%time
2 w_after = model_relu.get_weights()
3
4 h1_w = w_after[0].flatten().reshape(-1,1)
5 h2_w = w_after[2].flatten().reshape(-1,1)
6 out_w = w_after[4].flatten().reshape(-1,1)
7
8 fig = plt.figure()
9 plt.title("Weight matrices after model trained")
10 plt.subplot(1, 3, 1)
11 plt.title("Trained model Weights")
12 ax = sns.violinplot(y=h1_w,color='b')
13 plt.xlabel('Hidden Layer 1')
14
15 plt.subplot(1, 3, 2)
16 plt.title("Trained model Weights")
17 ax = sns.violinplot(y=h2_w, color='r')
18 plt.xlabel('Hidden Layer 2 ')
19
20 plt.subplot(1, 3, 3)
21 plt.title("Trained model Weights")
22 ax = sns.violinplot(y=out_w,color='y')
23 plt.xlabel('Output Layer ')
24 plt.show()
```



Summary:

In [81]:

```
1 from prettytable import PrettyTable
2 pt = PrettyTable()
3 pt.field_names = ["Activation", "optimizer", "BatchNormalization", "LossFunction", "Dropout", "Hidden Layers", "Test score", "Test accuracy"]
4 pt.add_row(["relu", "adam", "Yes", "Categorical Crossentropy Loss", "0.5", "2-(HiddenLayer)[430,322]", "0.051", "0.99"])
5 pt.add_row(["relu", "adam", "Yes", "Categorical Crossentropy Loss", "0.5", "3-(HiddenLayer)[320,270,162]", "0.061", "0.98"])
6 pt.add_row(["relu", "adam", "Yes", "Categorical Crossentropy Loss", "0.5", "5-(HiddenLayer)[340,190,112,72,38]", "0.079", "0.98"])
7 pt.add_row(["relu", "adam", "Yes", "Categorical Crossentropy Loss", "0.25", "2-(HiddenLayer)[430,322]", "0.061", "0.98"])
8 pt.add_row(["relu", "adam", "Yes", "Categorical Crossentropy Loss", "0.25", "3-(HiddenLayer)[320,270,162]", "0.063", "0.98"])
9 pt.add_row(["relu", "adam", "Yes", "Categorical Crossentropy Loss", "0.25", "5-(HiddenLayer)[340,190,112,72,38]", "0.070", "0.98"])
10 pt.add_row(["relu", "adam", "Yes", "mean_squared_error", "0.5", "2-(HiddenLayer)[430,322]", "0.003", "0.98"])
11 pt.add_row(["relu", "adam", "Yes", "mean_squared_error", "0.5", "3-(HiddenLayer)[320,270,162]", "0.003", "0.98"])
12 pt.add_row(["relu", "adam", "Yes", "mean_squared_error", "0.5", "5-(HiddenLayer)[340,190,112,72,38]", "0.004", "0.98"])
13 print(pt)
```

Activation	optimizer	BatchNormalization	LossFunction	Dropout	Hidden Layers	Test score	Test accuracy
relu	adam	Yes	Categorical Crossentropy Loss	0.5	2-(HiddenLayer)[430,322]	0.051	0.99
relu	adam	Yes	Categorical Crossentropy Loss	0.5	3-(HiddenLayer)[320,270,162]	0.061	0.98
relu	adam	Yes	Categorical Crossentropy Loss	0.5	5-(HiddenLayer)[340,190,112,72,38]	0.079	0.98
relu	adam	Yes	Categorical Crossentropy Loss	0.25	2-(HiddenLayer)[430,322]	0.061	0.98
relu	adam	Yes	Categorical Crossentropy Loss	0.25	3-(HiddenLayer)[320,270,162]	0.063	0.98
relu	adam	Yes	Categorical Crossentropy Loss	0.25	5-(HiddenLayer)[340,190,112,72,38]	0.070	0.98
relu	adam	Yes	mean_squared_error	0.5	2-(HiddenLayer)[430,322]	0.003	0.98
relu	adam	Yes	mean_squared_error	0.5	3-(HiddenLayer)[320,270,162]	0.003	0.98
relu	adam	Yes	mean_squared_error	0.5	5-(HiddenLayer)[340,190,112,72,38]	0.004	0.98

Conclusion:

1. From the above model we could see the Dropout (0.5) works well when compare to the Dropout(0.25).

2. Model test score and accuracy are good when we used the 0.5 as Dropout and Categorical Crossentropy as loss function.
3. Overall model perform well with Dropout 0.5 and with Epoch 20. For graphical representation i have increased the epoch value to 22 and also we see model get overfitting when epoch value increased more than 35.