

```
In [1]: 1 from keras.utils import np_utils
2 from keras.datasets import mnist
3 from keras.initializers import RandomNormal
4 import seaborn as sns
5
6 %matplotlib inline
7 import matplotlib.pyplot as plt
```

Using TensorFlow backend.

```
In [0]: 1 #Loading the training and the test data
2 (x_train,y_train),(x_test,y_test) = mnist.load_data()
```

```
In [3]: 1 #finding the shape of training and test data
2 print('Shape of training data is',x_train.shape[0],'and each image is of size {} x {}'.format(x_train.shape[
3 print('Shape of test data is ',x_test.shape[0],'and each image is of size {} x {}'.format(x_test.shape[1],x_
```

Shape of training data is 60000 and each image is of size 28 x 28  
Shape of test data is 10000 and each image is of size 28 x 28

```
In [0]: 1 #as the input image is of size 28*28 thats why we will convert each one of them to a 1*784 vector
2 #i.e each pixel represents a dimension of the image
3 #we will reshape the matrix
4
5 x_train = x_train.reshape(x_train.shape[0],x_train.shape[1]*x_train.shape[2])
6 x_test = x_test.reshape(x_test.shape[0],x_test.shape[1]*x_test.shape[2])
```

```
In [5]: 1 #shape of the data after converting from 3d to 2d
2
3 print('SHAPE OF TRAINING DATA IS: ',x_train.shape[0],'AND EACH IMAGE IS OF SIZE: ',x_train.shape[1])
4 print('SHAPE OF TEST DATA IS: ',x_test.shape[0],'EACH IMAGE IS OF SIZE: ',x_test.shape[1])
```

SHAPE OF TRAINING DATA IS: 60000 AND EACH IMAGE IS OF SIZE: 784  
SHAPE OF TEST DATA IS: 10000 EACH IMAGE IS OF SIZE: 784

```
In [6]: 1 #example data point
        2 print(x_train[0])
```

```
[ 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
  0  0  0  0  0  0  0  0  3  18  18  18  126  136  175  26  166  255
247 127  0  0  0  0  0  0  0  0  0  0  0  0  30  36  94  154
170 253 253 253 253 253 225 172 253 242 195  64  0  0  0  0  0
  0  0  0  0  0  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  80 156 107 253 253 205  11  0  43 154
  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
  0  14  1 154 253  90  0  0  0  0  0  0  0  0  0  0  0  0
  0  0  0  0  0  0  0  0  0  0  0  0  0  139 253 190  2  0
  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
  0  0  0  0  0  11 190 253  70  0  0  0  0  0  0  0  0  0
  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  35 241
225 160 108  1  0  0  0  0  0  0  0  0  0  0  0  0  0  0
  0  0  0  0  0  0  0  0  0  81 240 253 253 119  25  0  0  0
  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
  0  0  45 186 253 253 150  27  0  0  0  0  0  0  0  0  0  0
  0  0  0  0  0  0  0  0  0  0  0  0  0  16  93 252 253 187
  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
  0  0  0  0  0  0  0  249 253 249  64  0  0  0  0  0  0  0
  0  0  0  0  0  0  0  0  0  0  0  0  0  0  46 130 183 253
253 207  2  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
  0  0  0  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 0 0 0 0 0 0 0 0

```

```

In [0]: 1
        2 x_train = x_train/255
        3 x_test = x_test/255

```

```

In [8]: 1 print(x_train[0])

```

```

[0. 0. 0. 0. 0. 0.
 0. 0. 0. 0. 0. 0.
 0. 0. 0. 0. 0. 0.
 0. 0. 0. 0. 0. 0.
 0. 0. 0. 0. 0. 0.
 0. 0. 0. 0. 0. 0.
 0. 0. 0. 0. 0. 0.
 0. 0. 0. 0. 0. 0.
 0. 0. 0. 0. 0. 0.
 0. 0. 0. 0. 0. 0.
 0. 0. 0. 0. 0. 0.
 0. 0. 0. 0. 0. 0.
 0. 0. 0. 0. 0. 0.
 0. 0. 0. 0. 0. 0.
 0. 0. 0. 0. 0. 0.
 0. 0. 0. 0. 0. 0.]

```

```
In [9]: 1 #printing the class labels of some of the images
2 print('class label of first image',y_train[0])
3 print('class label of 11th image',y_train[10])
4 print('class label of 100th image',y_train[99])
5
6
7 #also we are converting here 10 class output to binary using to_categorical function of keras
8 #in a way we are performing one hot encoding on the output data
9
10 Y_train = np_utils.to_categorical(y_train,10)
11 Y_test = np_utils.to_categorical(y_test,10)
12
13 print('AFTER encoding')
14 print('output for first image is ',Y_train[0])
15 print('output for 11th image is ',Y_train[10])
16 print('output for 100th image is ',Y_train[99])
```

```
class label of first image 5
class label of 11th image 3
class label of 100th image 1
AFTER encoding
output for first image is [0. 0. 0. 0. 0. 1. 0. 0. 0. 0.]
output for 11th image is [0. 0. 0. 1. 0. 0. 0. 0. 0. 0.]
output for 100th image is [0. 1. 0. 0. 0. 0. 0. 0. 0. 0.]
```

## WE will use three different architectures for model implementation

- Model with 2 hidden layers
- Model with 3 hidden layers
- Model with 5 hidden layers

### In Each Architecture We will implement 4 models:

- MLP + Relu + Adam
- MLP + Relu + Adam + Dropout
- MLP + Relu + Adam + Batch Normalization
- MLP + Relu + Adam + Dropout + Batch Normalization

In each of the models we will perform hypereparameter tuning using GridSearch CV and Randomized cv

```
In [0]: 1 import warnings
2 warnings.filterwarnings('ignore')
3 from keras.models import Sequential
4 from keras.layers import Dense,Activation
5 #here we are importing the sequential and the dense,activation to specify about the fully connected MLP and
6
7
8 #some model parameters
9
10 output_dim = 10
11 input_dim = x_train.shape[1]
12 batch_size = 128
13 nb_epoch = 20
14
```

## 1. Architecture1: Model with 2 hidden layers:

input(784)-Relu(512)-Relu(256)-Output(10)

### 1.1 MLP + Relu + Adamoptimizer

```
In [11]: 1 """ for weight initialization we will initialize using He normalization
2 """
3 # for relu layers
4 # If we sample weights from a normal distribution  $N(0, \sigma)$  we satisfy this condition with  $\sigma = \sqrt{2/(n_i)}$ .
5 # h1 =>  $\sigma = \sqrt{2/(fan\_in)} = 0.062 \Rightarrow N(0, \sigma) = N(0, 0.062)$ 
6 # h2 =>  $\sigma = \sqrt{2/(fan\_in)} = 0.088 \Rightarrow N(0, \sigma) = N(0, 0.088)$ 
7 # out =>  $\sigma = \sqrt{2/(fan\_in+1)} = 0.120 \Rightarrow N(0, \sigma) = N(0, 0.120)$ 
8
9 model_relu = Sequential()
10 model_relu.add(Dense(512, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNormal(mean=
11 model_relu.add(Dense(256, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.088, seed=No
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_dat
```

WARNING: Logging before flag parsing goes to stderr.

W0827 14:22:42.262042 139961174951808 deprecation\_wrapper.py:119] From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow\_backend.py:74: The name tf.get\_default\_graph is deprecated. Please use tf.compat.v1.get\_default\_graph instead.

W0827 14:22:42.285037 139961174951808 deprecation\_wrapper.py:119] From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow\_backend.py:517: The name tf.placeholder is deprecated. Please use tf.compat.v1.placeholder instead.

W0827 14:22:42.289400 139961174951808 deprecation\_wrapper.py:119] From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow\_backend.py:4115: The name tf.random\_normal is deprecated. Please use tf.random.normal instead.

W0827 14:22:42.337172 139961174951808 deprecation\_wrapper.py:119] From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow\_backend.py:4138: The name tf.random\_uniform is deprecated. Please use tf.random.uniform instead.

W0827 14:22:42.357798 139961174951808 deprecation\_wrapper.py:119] From /usr/local/lib/python3.6/dist-packages/keras/optimizers.py:790: The name tf.train.Optimizer is deprecated. Please use tf.compat.v1.train.Optimizer instead.

W0827 14:22:42.384944 139961174951808 deprecation\_wrapper.py:119] From /usr/local/lib/python3.6/dist-packages/keras/optimizers.py:790: The name tf.train.Optimizer is deprecated. Please use tf.compat.v1.train.Optimizer instead.

eras/backend/tensorflow\_backend.py:3295: The name tf.log is deprecated. Please use tf.math.log instead.

W0827 14:22:42.495736 139961174951808 deprecation.py:323] From /usr/local/lib/python3.6/dist-packages/tensorflow/python/ops/math\_grad.py:1250: add\_dispatch\_support.<locals>.wrapper (from tensorflow.python.ops.array\_ops) is deprecated and will be removed in a future version.

Instructions for updating:

Use tf.where in 2.0, which has the same broadcast rule as np.where

Layer (type)	Output Shape	Param #
dense_1 (Dense)	(None, 512)	401920
dense_2 (Dense)	(None, 256)	131328
dense_3 (Dense)	(None, 10)	2570

=====  
Total params: 535,818

Trainable params: 535,818

Non-trainable params: 0

None

Train on 60000 samples, validate on 10000 samples

Epoch 1/20

60000/60000 [=====] - 4s 67us/step - loss: 0.2184 - acc: 0.9336 - val\_loss: 0.1089  
- val\_acc: 0.9656

Epoch 2/20

60000/60000 [=====] - 3s 51us/step - loss: 0.0821 - acc: 0.9752 - val\_loss: 0.0842  
- val\_acc: 0.9735

Epoch 3/20

60000/60000 [=====] - 3s 51us/step - loss: 0.0503 - acc: 0.9843 - val\_loss: 0.0760  
- val\_acc: 0.9763

Epoch 4/20

60000/60000 [=====] - 3s 52us/step - loss: 0.0347 - acc: 0.9891 - val\_loss: 0.0828  
- val\_acc: 0.9747

Epoch 5/20

60000/60000 [=====] - 3s 50us/step - loss: 0.0259 - acc: 0.9919 - val\_loss: 0.0734  
- val\_acc: 0.9780

Epoch 6/20

60000/60000 [=====] - 3s 53us/step - loss: 0.0199 - acc: 0.9937 - val\_loss: 0.0757  
- val\_acc: 0.9773

Epoch 7/20

60000/60000 [=====] - 3s 51us/step - loss: 0.0180 - acc: 0.9942 - val\_loss: 0.0632

```
- val_acc: 0.9815
Epoch 8/20
60000/60000 [=====] - 3s 51us/step - loss: 0.0128 - acc: 0.9961 - val_loss: 0.0935
- val_acc: 0.9752
Epoch 9/20
60000/60000 [=====] - 3s 53us/step - loss: 0.0184 - acc: 0.9937 - val_loss: 0.0893
- val_acc: 0.9789
Epoch 10/20
60000/60000 [=====] - 3s 50us/step - loss: 0.0125 - acc: 0.9958 - val_loss: 0.0877
- val_acc: 0.9784
Epoch 11/20
60000/60000 [=====] - 3s 51us/step - loss: 0.0113 - acc: 0.9965 - val_loss: 0.0981
- val_acc: 0.9779
Epoch 12/20
60000/60000 [=====] - 3s 51us/step - loss: 0.0102 - acc: 0.9967 - val_loss: 0.0787
- val_acc: 0.9815
Epoch 13/20
60000/60000 [=====] - 3s 51us/step - loss: 0.0104 - acc: 0.9967 - val_loss: 0.0783
- val_acc: 0.9820
Epoch 14/20
60000/60000 [=====] - 3s 51us/step - loss: 0.0062 - acc: 0.9978 - val_loss: 0.0900
- val_acc: 0.9810
Epoch 15/20
60000/60000 [=====] - 3s 53us/step - loss: 0.0113 - acc: 0.9962 - val_loss: 0.0954
- val_acc: 0.9787
Epoch 16/20
60000/60000 [=====] - 3s 54us/step - loss: 0.0089 - acc: 0.9971 - val_loss: 0.0846
- val_acc: 0.9823
Epoch 17/20
60000/60000 [=====] - 3s 57us/step - loss: 0.0089 - acc: 0.9972 - val_loss: 0.0924
- val_acc: 0.9794
Epoch 18/20
60000/60000 [=====] - 3s 57us/step - loss: 0.0070 - acc: 0.9978 - val_loss: 0.0989
- val_acc: 0.9795
Epoch 19/20
60000/60000 [=====] - 3s 55us/step - loss: 0.0101 - acc: 0.9969 - val_loss: 0.0958
- val_acc: 0.9804
Epoch 20/20
60000/60000 [=====] - 3s 51us/step - loss: 0.0071 - acc: 0.9978 - val_loss: 0.0965
- val_acc: 0.9811
```



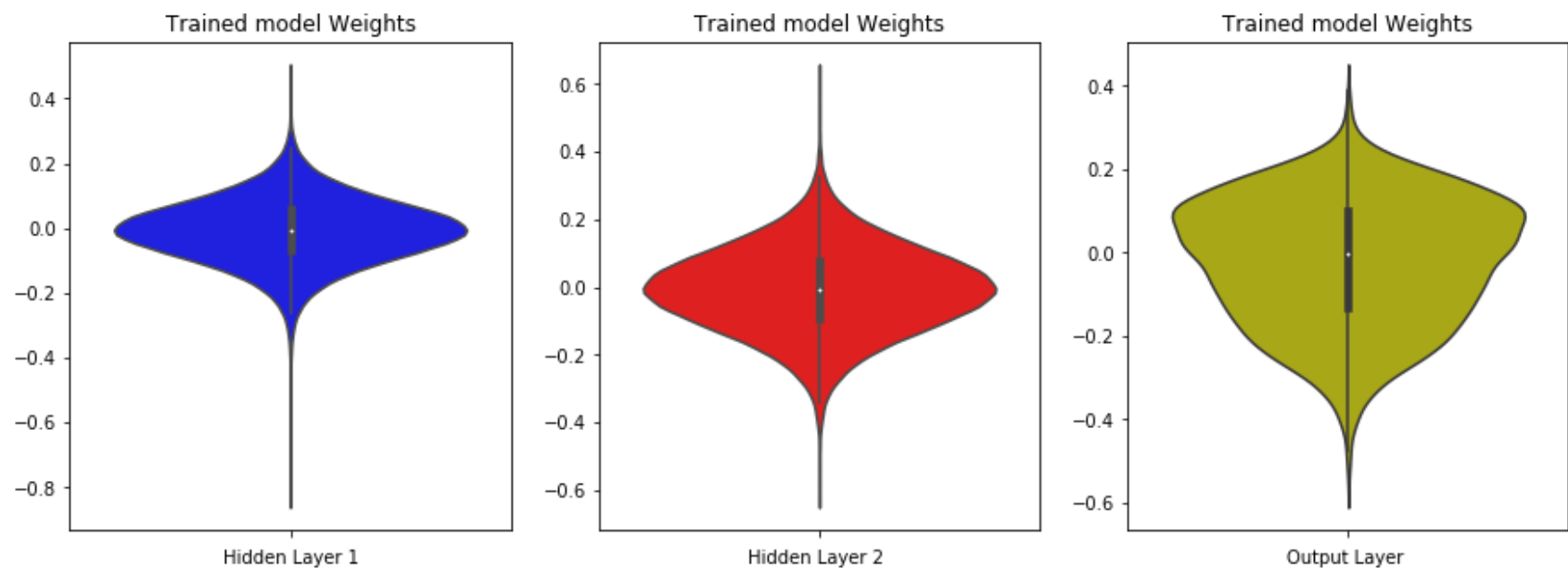
```
In [12]: 1 #evaluation on test data
          2
          3 score = model_relu.evaluate(x_test,Y_test,verbose = 1)
          4 print('Loss on test data is: ',score[0])
          5 print('accuracy on test data is: ',score[1])
```

```
10000/10000 [=====] - 1s 53us/step
Loss on test data is:  0.09651037384942601
accuracy on test data is:  0.9811
```

```
In [0]: 1 import pickle
          2 def savetofile(obj,filename):
          3     pickle.dump(obj,open(filename+".p",'wb'))
          4
          5 def openfromfile(filename):
          6     temp = pickle.load(open(filename+".p",'rb'))
          7     return temp
```

```
In [0]: 1
2 def violin_plot(dl_model):
3     w_after= dl_model.get_weights()
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
9     fig = plt.figure(figsize = (15,5))
10    plt.title("Weight matrices after model trained")
11    plt.subplot(1, 3, 1)
12    plt.title("Trained model Weights")
13    ax = sns.violinplot(y=h1_w,color='b')
14    plt.xlabel('Hidden Layer 1')
15
16    plt.subplot(1, 3, 2)
17    plt.title("Trained model Weights")
18    ax = sns.violinplot(y=h2_w, color='r')
19    plt.xlabel('Hidden Layer 2 ')
20
21    plt.subplot(1, 3, 3)
22    plt.title("Trained model Weights")
23    ax = sns.violinplot(y=out_w,color='y')
24    plt.xlabel('Output Layer ')
25    plt.show()
```

```
In [16]: 1 violin_plot(model_relu)
```



```
In [0]: 1 arch_1_model_1 = savetofile(history, 'arch_1_model_1')
```

## 1.2 MLP + Relu + Adamoptimizer + dropout

```
In [19]: 1 from keras.layers import Dropout
2 model_relu_drop = Sequential()
3
4 model_relu_drop.add(Dense(512,activation = 'relu',input_shape = (input_dim,), kernel_initializer = RandomNormal(mean = 0.0,stddev = 0.08)))
5 model_relu_drop.add(Dropout(0.5))
6 #adding the dropout layer for each layer
7
8 model_relu_drop.add(Dense(256,activation = 'relu',kernel_initializer = RandomNormal(mean = 0.0,stddev = 0.08)))
9 model_relu_drop.add(Dropout(0.5))
10
11
12 model_relu_drop.add(Dense(output_dim,activation = 'softmax'))
13 print(model_relu_drop.summary())
14
15 model_relu_drop.compile(optimizer = 'adam',loss = 'categorical_crossentropy',metrics = ['accuracy'])
16 history = model_relu_drop.fit(x_train,Y_train,batch_size = batch_size,epochs = nb_epoch,verbose = 1,validation_data=(x_test,y_test))
17
18
```

W0827 14:28:45.499598 139961174951808 deprecation.py:506] From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow\_backend.py:3445: calling dropout (from tensorflow.python.ops.nn\_ops) with keep\_prob is deprecated and will be removed in a future version.

Instructions for updating:

Please use `rate` instead of `keep\_prob`. Rate should be set to `rate = 1 - keep\_prob`.

Layer (type)	Output Shape	Param #
dense_4 (Dense)	(None, 512)	401920
dropout_1 (Dropout)	(None, 512)	0
dense_5 (Dense)	(None, 256)	131328
dropout_2 (Dropout)	(None, 256)	0
dense_6 (Dense)	(None, 10)	2570
Total params: 535,818		
Trainable params: 535,818		
Non-trainable params: 0		

None

Train on 60000 samples, validate on 10000 samples

Epoch 1/20

60000/60000 [=====] - 3s 56us/step - loss: 0.4535 - acc: 0.8571 - val\_loss: 0.1509 - val\_acc: 0.9526

Epoch 2/20

60000/60000 [=====] - 3s 54us/step - loss: 0.2033 - acc: 0.9391 - val\_loss: 0.1025 - val\_acc: 0.9680

Epoch 3/20

60000/60000 [=====] - 3s 54us/step - loss: 0.1537 - acc: 0.9540 - val\_loss: 0.0862 - val\_acc: 0.9721

Epoch 4/20

60000/60000 [=====] - 3s 54us/step - loss: 0.1307 - acc: 0.9603 - val\_loss: 0.0781 - val\_acc: 0.9761

Epoch 5/20

60000/60000 [=====] - 3s 55us/step - loss: 0.1137 - acc: 0.9660 - val\_loss: 0.0754 - val\_acc: 0.9763

Epoch 6/20

60000/60000 [=====] - 3s 54us/step - loss: 0.1003 - acc: 0.9696 - val\_loss: 0.0711 - val\_acc: 0.9772

Epoch 7/20

60000/60000 [=====] - 3s 58us/step - loss: 0.0957 - acc: 0.9706 - val\_loss: 0.0658 - val\_acc: 0.9801

Epoch 8/20

60000/60000 [=====] - 3s 56us/step - loss: 0.0860 - acc: 0.9743 - val\_loss: 0.0654 - val\_acc: 0.9791

Epoch 9/20

60000/60000 [=====] - 3s 55us/step - loss: 0.0782 - acc: 0.9752 - val\_loss: 0.0686 - val\_acc: 0.9793

Epoch 10/20

60000/60000 [=====] - 3s 57us/step - loss: 0.0756 - acc: 0.9766 - val\_loss: 0.0648 - val\_acc: 0.9803

Epoch 11/20

60000/60000 [=====] - 3s 58us/step - loss: 0.0709 - acc: 0.9780 - val\_loss: 0.0611 - val\_acc: 0.9827

Epoch 12/20

60000/60000 [=====] - 3s 57us/step - loss: 0.0662 - acc: 0.9795 - val\_loss: 0.0585 - val\_acc: 0.9828

Epoch 13/20

60000/60000 [=====] - 3s 55us/step - loss: 0.0611 - acc: 0.9810 - val\_loss: 0.0616 - val\_acc: 0.9827

Epoch 14/20

60000/60000 [=====] - 3s 56us/step - loss: 0.0610 - acc: 0.9803 - val\_loss: 0.0604 - val\_acc: 0.9827

```

al_acc: 0.9821
Epoch 15/20
60000/60000 [=====] - 3s 55us/step - loss: 0.0569 - acc: 0.9823 - val_loss: 0.0633 - v
al_acc: 0.9829
Epoch 16/20
60000/60000 [=====] - 3s 55us/step - loss: 0.0573 - acc: 0.9820 - val_loss: 0.0608 - v
al_acc: 0.9837
Epoch 17/20
60000/60000 [=====] - 3s 55us/step - loss: 0.0543 - acc: 0.9827 - val_loss: 0.0571 - v
al_acc: 0.9842
Epoch 18/20
60000/60000 [=====] - 3s 56us/step - loss: 0.0502 - acc: 0.9835 - val_loss: 0.0579 - v
al_acc: 0.9843
Epoch 19/20
60000/60000 [=====] - 3s 54us/step - loss: 0.0527 - acc: 0.9835 - val_loss: 0.0584 - v
al_acc: 0.9840
Epoch 20/20
60000/60000 [=====] - 3s 55us/step - loss: 0.0475 - acc: 0.9850 - val_loss: 0.0589 - v
al_acc: 0.9847

```

```

In [20]: 1 score = model_relu_drop.evaluate(x_test,Y_test,verbose = 1)
         2 print('Loss on test data is: ',score[0])
         3 print('accuracy on test data is: ',score[1])

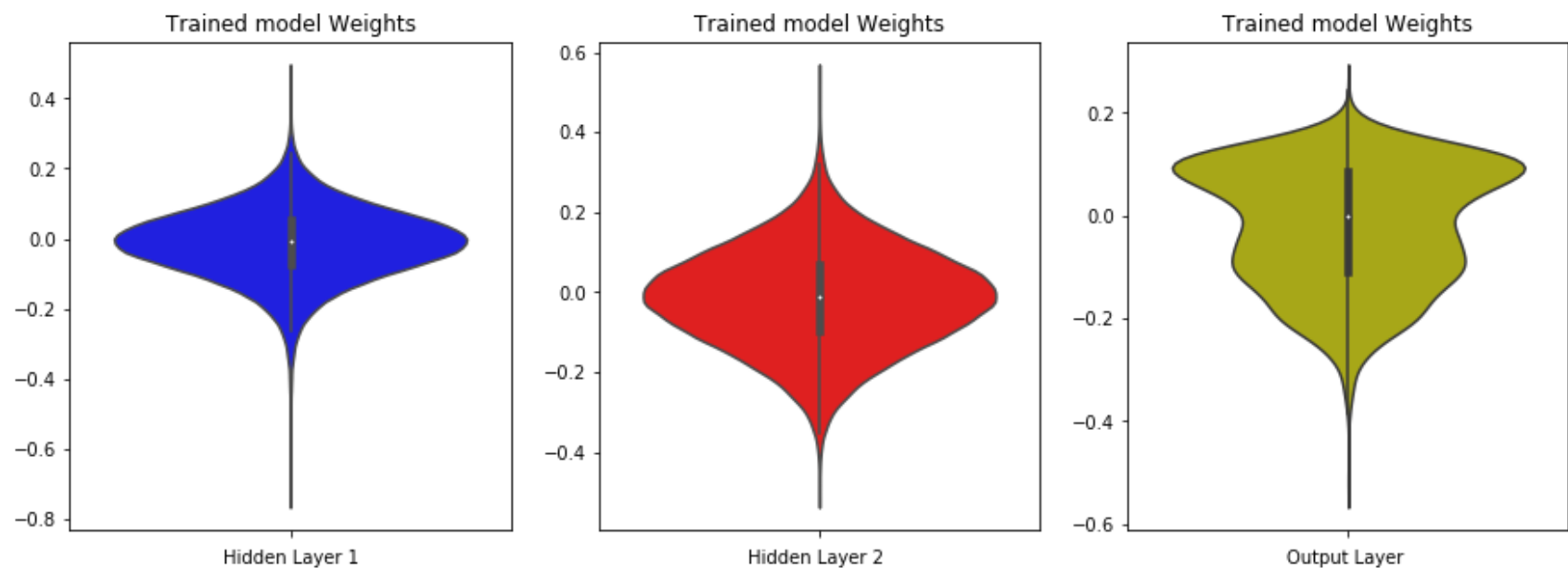
```

```

10000/10000 [=====] - 1s 53us/step
Loss on test data is: 0.058890673811543455
accuracy on test data is: 0.9847

```

```
In [21]: 1 violin_plot(model_relu_drop)
```



```
In [0]: 1 arch_1_model_2 = savetofile(history, 'arch_1_model_2')
```

### 1.3 MLP + Relu + Adamoptimizer + BatchNormalization

```
In [23]: 1 from keras.layers import BatchNormalization
2
3 model_relu_batch = Sequential()
4 model_relu_batch.add(Dense(512,activation = 'relu',input_shape = (input_dim,),kernel_initializer = RandomNormal(mean = 0.0,stddev = 0.01)))
5 model_relu_batch.add(BatchNormalization())
6
7 model_relu_batch.add(Dense(256,activation = 'relu',kernel_initializer = RandomNormal(mean = 0.0,stddev = 0.01)))
8 model_relu_batch.add(BatchNormalization())
9
10 model_relu_batch.add(Dense(output_dim,activation = 'softmax'))
11 print(model_relu_batch.summary())
12
13
14 model_relu_batch.compile(optimizer = 'adam',loss = 'categorical_crossentropy',metrics = ['accuracy'])
15 history = model_relu_batch.fit(x_train,Y_train,batch_size = batch_size,epochs = nb_epoch,verbose = 1,validation_data=(x_test,Y_test))
16
```

Layer (type)	Output Shape	Param #
dense_7 (Dense)	(None, 512)	401920
batch_normalization_1 (Batch Normalization)	(None, 512)	2048
dense_8 (Dense)	(None, 256)	131328
batch_normalization_2 (Batch Normalization)	(None, 256)	1024
dense_9 (Dense)	(None, 10)	2570
Total params: 538,890		
Trainable params: 537,354		
Non-trainable params: 1,536		

None

Train on 60000 samples, validate on 10000 samples

Epoch 1/20

60000/60000 [=====] - 6s 93us/step - loss: 0.1855 - acc: 0.9443 - val\_loss: 0.0889 - val\_acc: 0.9716

Epoch 2/20

60000/60000 [=====] - 5s 82us/step - loss: 0.0671 - acc: 0.9799 - val\_loss: 0.0789 - val\_acc: 0.9716



```
al_acc: 0.9741
Epoch 3/20
60000/60000 [=====] - 5s 82us/step - loss: 0.0414 - acc: 0.9875 - val_loss: 0.0822 - v
al_acc: 0.9726
Epoch 4/20
60000/60000 [=====] - 5s 83us/step - loss: 0.0305 - acc: 0.9901 - val_loss: 0.0771 - v
al_acc: 0.9767
Epoch 5/20
60000/60000 [=====] - 5s 81us/step - loss: 0.0228 - acc: 0.9929 - val_loss: 0.0761 - v
al_acc: 0.9761
Epoch 6/20
60000/60000 [=====] - 5s 81us/step - loss: 0.0198 - acc: 0.9936 - val_loss: 0.0837 - v
al_acc: 0.9759
Epoch 7/20
60000/60000 [=====] - 5s 85us/step - loss: 0.0213 - acc: 0.9930 - val_loss: 0.0885 - v
al_acc: 0.9739
Epoch 8/20
60000/60000 [=====] - 5s 85us/step - loss: 0.0168 - acc: 0.9946 - val_loss: 0.0790 - v
al_acc: 0.9778
Epoch 9/20
60000/60000 [=====] - 5s 85us/step - loss: 0.0128 - acc: 0.9959 - val_loss: 0.0789 - v
al_acc: 0.9779
Epoch 10/20
60000/60000 [=====] - 5s 83us/step - loss: 0.0126 - acc: 0.9961 - val_loss: 0.0750 - v
al_acc: 0.9800
Epoch 11/20
60000/60000 [=====] - 5s 83us/step - loss: 0.0113 - acc: 0.9963 - val_loss: 0.0772 - v
al_acc: 0.9792
Epoch 12/20
60000/60000 [=====] - 5s 83us/step - loss: 0.0122 - acc: 0.9960 - val_loss: 0.0862 - v
al_acc: 0.9782
Epoch 13/20
60000/60000 [=====] - 5s 84us/step - loss: 0.0099 - acc: 0.9968 - val_loss: 0.0818 - v
al_acc: 0.9784
Epoch 14/20
60000/60000 [=====] - 5s 84us/step - loss: 0.0091 - acc: 0.9971 - val_loss: 0.0866 - v
al_acc: 0.9800
Epoch 15/20
60000/60000 [=====] - 5s 84us/step - loss: 0.0085 - acc: 0.9974 - val_loss: 0.0882 - v
al_acc: 0.9785
Epoch 16/20
60000/60000 [=====] - 5s 81us/step - loss: 0.0071 - acc: 0.9975 - val_loss: 0.0876 - v
al_acc: 0.9781
```

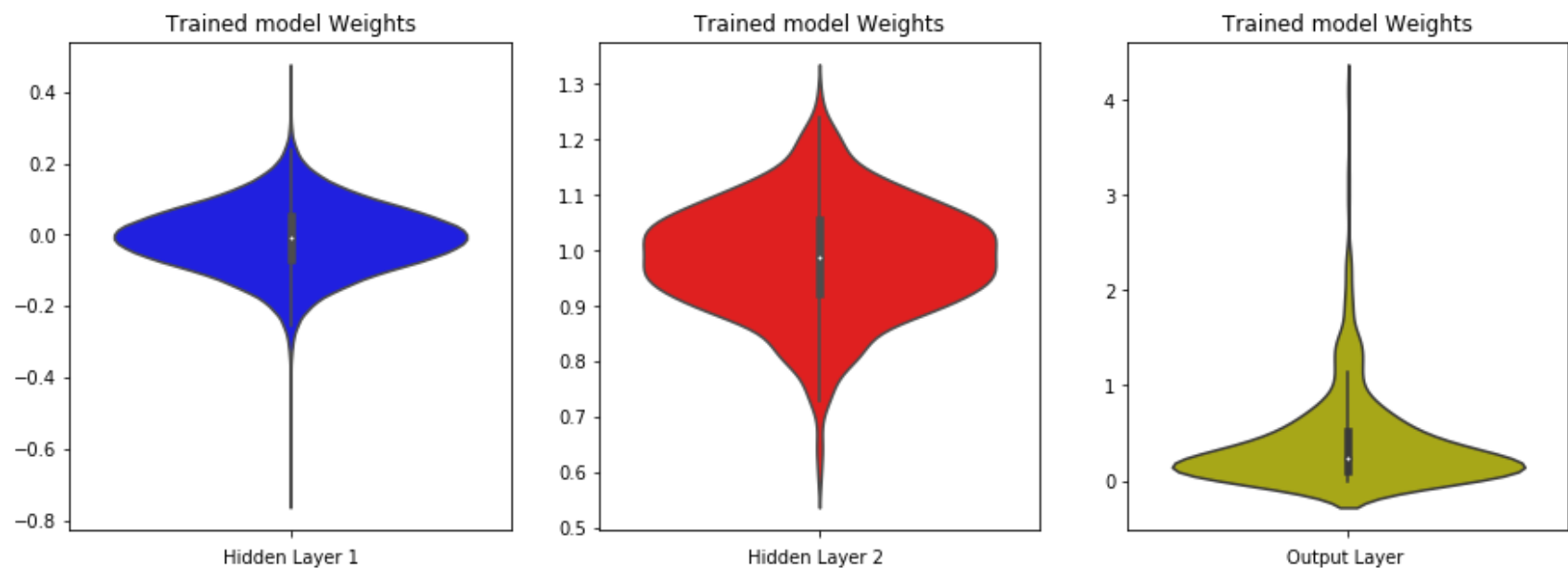
```
Epoch 17/20
60000/60000 [=====] - 5s 82us/step - loss: 0.0080 - acc: 0.9972 - val_loss: 0.0940 - val_acc: 0.9783
Epoch 18/20
60000/60000 [=====] - 5s 82us/step - loss: 0.0118 - acc: 0.9960 - val_loss: 0.0801 - val_acc: 0.9813
Epoch 19/20
60000/60000 [=====] - 5s 84us/step - loss: 0.0070 - acc: 0.9979 - val_loss: 0.0739 - val_acc: 0.9830
Epoch 20/20
60000/60000 [=====] - 5s 83us/step - loss: 0.0087 - acc: 0.9974 - val_loss: 0.0840 - val_acc: 0.9798
```

In [24]:

```
1 score = model_relu_batch.evaluate(x_test,Y_test,verbose = 1)
2 print('Loss on the test data is: ',score[0])
3 print('Accuracy on the test data is:',score[1])
4
```

```
10000/10000 [=====] - 1s 64us/step
Loss on the test data is: 0.0839915322766581
Accuracy on the test data is: 0.9798
```

```
In [25]: 1 violin_plot(model_relu_batch)
```



```
In [0]: 1 arch_1_mode_3 = savetofile(history, 'arch_1_model_3')
```

## 1.4 MLP + Relu + Adamoptimizer + BatchNormalization +Dropout

```
In [27]: 1 model_relu_batch_drop = Sequential()
2 model_relu_batch_drop.add(Dense(512,activation = 'relu',input_shape = (input_dim,),kernel_initializer = Rand
3 model_relu_batch_drop.add(BatchNormalization())
4 model_relu_batch_drop.add(Dropout(0.5))
5
6
7 model_relu_batch_drop.add(Dense(256,activation = 'relu',kernel_initializer = RandomNormal(mean = 0.0,stddev
8 model_relu_batch_drop.add(BatchNormalization())
9 model_relu_batch_drop.add(Dropout(0.5))
10
11
12 model_relu_batch_drop.add(Dense(output_dim,activation = 'softmax'))
13 print(model_relu_batch_drop.summary())
14
15 model_relu_batch_drop.compile(optimizer = 'adam',loss = 'categorical_crossentropy',metrics = ['accuracy'])
16 history = model_relu_batch_drop.fit(x_train,Y_train,batch_size = batch_size,epochs = nb_epoch,verbose = 1,va
```

Layer (type)	Output Shape	Param #
dense_10 (Dense)	(None, 512)	401920
batch_normalization_3 (Batch Normalization)	(None, 512)	2048
dropout_3 (Dropout)	(None, 512)	0
dense_11 (Dense)	(None, 256)	131328
batch_normalization_4 (Batch Normalization)	(None, 256)	1024
dropout_4 (Dropout)	(None, 256)	0
dense_12 (Dense)	(None, 10)	2570
Total params: 538,890		
Trainable params: 537,354		
Non-trainable params: 1,536		

None  
Train on 60000 samples, validate on 10000 samples  
Epoch 1/20

```
60000/60000 [=====] - 6s 100us/step - loss: 0.4389 - acc: 0.8669 - val_loss: 0.1409 - val_acc: 0.9577
Epoch 2/20
60000/60000 [=====] - 5s 88us/step - loss: 0.2087 - acc: 0.9364 - val_loss: 0.1097 - val_acc: 0.9651
Epoch 3/20
60000/60000 [=====] - 5s 86us/step - loss: 0.1626 - acc: 0.9494 - val_loss: 0.0911 - val_acc: 0.9713
Epoch 4/20
60000/60000 [=====] - 5s 85us/step - loss: 0.1358 - acc: 0.9578 - val_loss: 0.0831 - val_acc: 0.9743
Epoch 5/20
60000/60000 [=====] - 5s 87us/step - loss: 0.1191 - acc: 0.9632 - val_loss: 0.0717 - val_acc: 0.9764
Epoch 6/20
60000/60000 [=====] - 5s 87us/step - loss: 0.1086 - acc: 0.9653 - val_loss: 0.0715 - val_acc: 0.9774
Epoch 7/20
60000/60000 [=====] - 5s 86us/step - loss: 0.0967 - acc: 0.9699 - val_loss: 0.0666 - val_acc: 0.9784
Epoch 8/20
60000/60000 [=====] - 5s 87us/step - loss: 0.0905 - acc: 0.9710 - val_loss: 0.0629 - val_acc: 0.9802
Epoch 9/20
60000/60000 [=====] - 5s 86us/step - loss: 0.0853 - acc: 0.9730 - val_loss: 0.0667 - val_acc: 0.9804
Epoch 10/20
60000/60000 [=====] - 5s 88us/step - loss: 0.0817 - acc: 0.9743 - val_loss: 0.0570 - val_acc: 0.9820
Epoch 11/20
60000/60000 [=====] - 5s 86us/step - loss: 0.0735 - acc: 0.9763 - val_loss: 0.0621 - val_acc: 0.9823
Epoch 12/20
60000/60000 [=====] - 5s 89us/step - loss: 0.0695 - acc: 0.9775 - val_loss: 0.0576 - val_acc: 0.9831
Epoch 13/20
60000/60000 [=====] - 5s 86us/step - loss: 0.0649 - acc: 0.9787 - val_loss: 0.0604 - val_acc: 0.9834
Epoch 14/20
60000/60000 [=====] - 5s 88us/step - loss: 0.0621 - acc: 0.9804 - val_loss: 0.0583 - val_acc: 0.9828
Epoch 15/20
60000/60000 [=====] - 5s 88us/step - loss: 0.0614 - acc: 0.9798 - val_loss: 0.0581 - val_acc: 0.9828
```

```

al_acc: 0.9825
Epoch 16/20
60000/60000 [=====] - 5s 89us/step - loss: 0.0584 - acc: 0.9813 - val_loss: 0.0557 - v
al_acc: 0.9841
Epoch 17/20
60000/60000 [=====] - 5s 88us/step - loss: 0.0563 - acc: 0.9818 - val_loss: 0.0537 - v
al_acc: 0.9840
Epoch 18/20
60000/60000 [=====] - 5s 88us/step - loss: 0.0566 - acc: 0.9815 - val_loss: 0.0601 - v
al_acc: 0.9825
Epoch 19/20
60000/60000 [=====] - 5s 87us/step - loss: 0.0505 - acc: 0.9837 - val_loss: 0.0553 - v
al_acc: 0.9838
Epoch 20/20
60000/60000 [=====] - 5s 86us/step - loss: 0.0469 - acc: 0.9848 - val_loss: 0.0551 - v
al_acc: 0.9846

```

```

In [28]: 1 score = model_relu_batch_drop.evaluate(x_test,Y_test)
          2 print('loss on test data is:',score[0])
          3 print('accuracy on test data is',score[1])

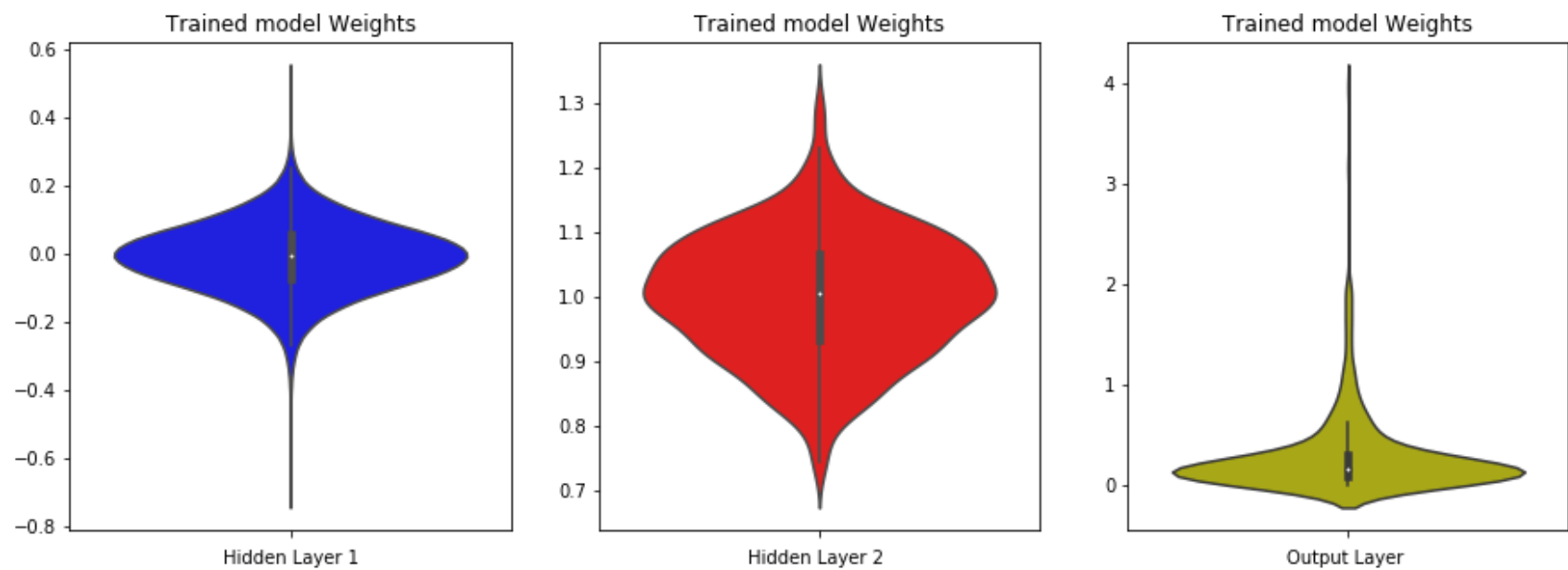
```

```

10000/10000 [=====] - 1s 68us/step
loss on test data is: 0.05505812452407554
accuracy on test data is 0.9846

```

```
In [29]: 1 violin_plot(model_relu_batch_drop)
```



```
In [0]: 1 arch_1_model_4 = savetofile(history, 'arch_1_model_4')
```

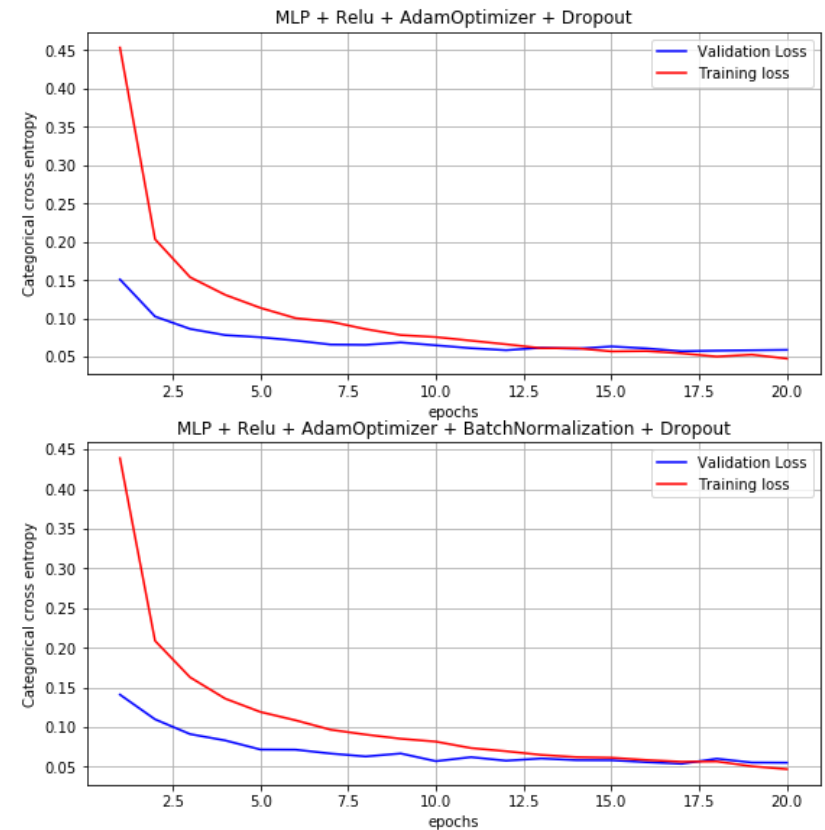
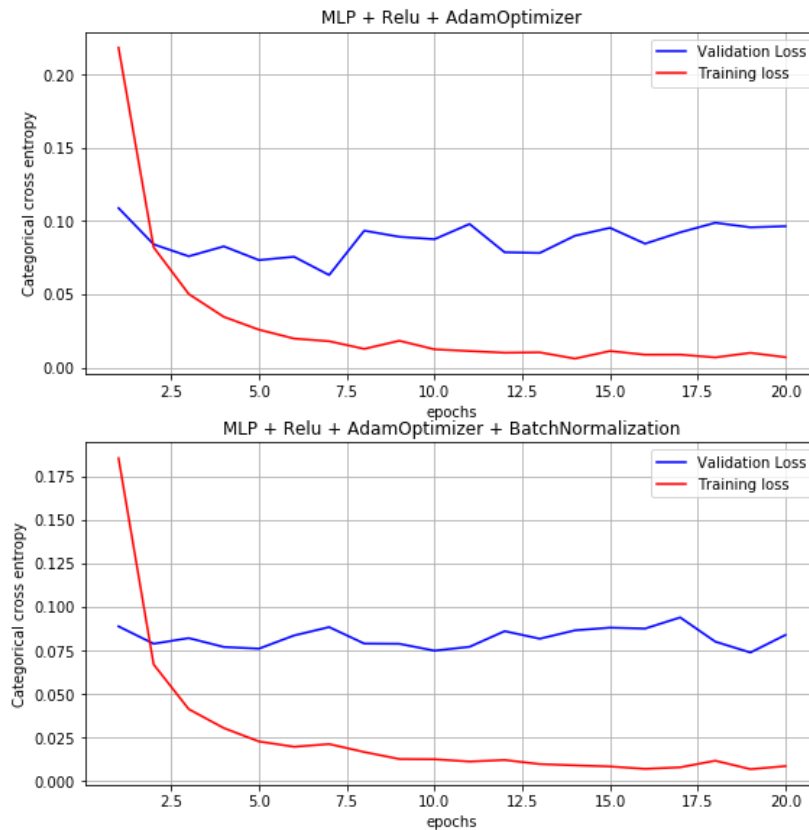
```
In [31]: 1 #plotting for all 4 models
2
3 plt.figure(figsize = (20,20))
4 plt.grid()
5 x = list(range(1,nb_epoch+1))
6
7 """MODEL 1"""
8 plt.subplot(4,2,1)
9 plt.title('MLP + Relu + AdamOptimizer')
10 plt.grid()
11 plt.plot(x,openfromfile('arch_1_model_1').history['val_loss'],color = 'b',label = 'Validation Loss')
12 plt.plot(x,openfromfile('arch_1_model_1').history['loss'],color = 'r',label = 'Training loss')
13 plt.xlabel('epochs')
14 plt.ylabel('Categorical cross entropy')
15 plt.legend()
16
17
18 """MODEL 2"""
19
20 plt.subplot(4,2,2)
21 plt.title('MLP + Relu + AdamOptimizer + Dropout')
22 plt.grid()
23 plt.plot(x,openfromfile('arch_1_model_2').history['val_loss'],color = 'b',label = 'Validation Loss')
24 plt.plot(x,openfromfile('arch_1_model_2').history['loss'],color = 'r',label = 'Training loss')
25 plt.xlabel('epochs')
26 plt.ylabel('Categorical cross entropy')
27 plt.legend()
28
29
30
31 """MODEL 3"""
32 plt.subplot(4,2,3)
33 plt.title('MLP + Relu + AdamOptimizer + BatchNormalization')
34 plt.grid()
35 plt.plot(x,openfromfile('arch_1_model_3').history['val_loss'],color = 'b',label = 'Validation Loss')
36 plt.plot(x,openfromfile('arch_1_model_3').history['loss'],color = 'r',label = 'Training loss')
37 plt.xlabel('epochs')
38 plt.ylabel('Categorical cross entropy')
39 plt.legend()
40
41
42 """MODEL 4"""
```



```

43 plt.subplot(4,2,4)
44 plt.title('MLP + Relu + AdamOptimizer + BatchNormalization + Dropout')
45 plt.grid()
46 plt.plot(x,openfromfile('arch_1_model_4').history['val_loss'],color = 'b',label = 'Validation Loss')
47 plt.plot(x,openfromfile('arch_1_model_4').history['loss'],color = 'r',label = 'Training loss')
48 plt.xlabel('epochs')
49 plt.ylabel('Categorical cross entropy')
50 plt.legend()
51 plt.show()

```



## 2. ARCHITECTURE 2: Model with 3 hidden layers

Input(786) - relu(1000) - relu(500)-relu(250)-softmax(10)

```
In [0]: 1 ### Model 1: MLP + Relu + Adamoptimizer
```

In [33]:

```

1
2
3 # for relu layers
4 from keras.initializers import he_normal
5
6 model_relu = Sequential()
7 model_relu.add(Dense(1000, activation='relu', input_shape=(input_dim,), kernel_initializer=he_normal(seed =
8 model_relu.add(Dense(500, activation='relu', kernel_initializer=he_normal(seed=None)))
9 model_relu.add(Dense(250, activation='relu', kernel_initializer=he_normal(seed=None)))
10 model_relu.add(Dense(output_dim, activation='softmax'))
11
12 print(model_relu.summary())
13
14 model_relu.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
15
16 history = model_relu.fit(x_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, validation_dat
17

```

Layer (type)	Output Shape	Param #
dense_13 (Dense)	(None, 1000)	785000
dense_14 (Dense)	(None, 500)	500500
dense_15 (Dense)	(None, 250)	125250
dense_16 (Dense)	(None, 10)	2510
Total params: 1,413,260		
Trainable params: 1,413,260		
Non-trainable params: 0		

None

Train on 60000 samples, validate on 10000 samples

Epoch 1/20

60000/60000 [=====] - 6s 96us/step - loss: 0.1955 - acc: 0.9404 - val\_loss: 0.0872 - val\_acc: 0.9739

Epoch 2/20

60000/60000 [=====] - 4s 70us/step - loss: 0.0765 - acc: 0.9768 - val\_loss: 0.0833 - val\_acc: 0.9733

```
Epoch 3/20
60000/60000 [=====] - 4s 71us/step - loss: 0.0501 - acc: 0.9835 - val_loss: 0.0751 - val_acc: 0.9767
Epoch 4/20
60000/60000 [=====] - 4s 71us/step - loss: 0.0380 - acc: 0.9879 - val_loss: 0.0693 - val_acc: 0.9806
Epoch 5/20
60000/60000 [=====] - 4s 73us/step - loss: 0.0297 - acc: 0.9906 - val_loss: 0.0716 - val_acc: 0.9803
Epoch 6/20
60000/60000 [=====] - 4s 71us/step - loss: 0.0258 - acc: 0.9916 - val_loss: 0.0795 - val_acc: 0.9777
Epoch 7/20
60000/60000 [=====] - 4s 71us/step - loss: 0.0213 - acc: 0.9930 - val_loss: 0.0797 - val_acc: 0.9797
Epoch 8/20
60000/60000 [=====] - 4s 73us/step - loss: 0.0167 - acc: 0.9947 - val_loss: 0.0774 - val_acc: 0.9798
Epoch 9/20
60000/60000 [=====] - 5s 76us/step - loss: 0.0193 - acc: 0.9935 - val_loss: 0.0741 - val_acc: 0.9818
Epoch 10/20
60000/60000 [=====] - 5s 76us/step - loss: 0.0167 - acc: 0.9947 - val_loss: 0.0844 - val_acc: 0.9785
Epoch 11/20
60000/60000 [=====] - 4s 73us/step - loss: 0.0141 - acc: 0.9956 - val_loss: 0.0713 - val_acc: 0.9823
Epoch 12/20
60000/60000 [=====] - 5s 76us/step - loss: 0.0123 - acc: 0.9962 - val_loss: 0.0977 - val_acc: 0.9771
Epoch 13/20
60000/60000 [=====] - 5s 76us/step - loss: 0.0123 - acc: 0.9964 - val_loss: 0.0915 - val_acc: 0.9809
Epoch 14/20
60000/60000 [=====] - 4s 73us/step - loss: 0.0138 - acc: 0.9957 - val_loss: 0.0800 - val_acc: 0.9821
Epoch 15/20
60000/60000 [=====] - 4s 72us/step - loss: 0.0059 - acc: 0.9983 - val_loss: 0.0838 - val_acc: 0.9825
Epoch 16/20
60000/60000 [=====] - 4s 70us/step - loss: 0.0167 - acc: 0.9952 - val_loss: 0.0834 - val_acc: 0.9831
Epoch 17/20
```

```

60000/60000 [=====] - 4s 70us/step - loss: 0.0077 - acc: 0.9975 - val_loss: 0.1016 - v
al_acc: 0.9804
Epoch 18/20
60000/60000 [=====] - 4s 71us/step - loss: 0.0140 - acc: 0.9958 - val_loss: 0.1018 - v
al_acc: 0.9777
Epoch 19/20
60000/60000 [=====] - 4s 72us/step - loss: 0.0067 - acc: 0.9981 - val_loss: 0.0938 - v
al_acc: 0.9832
Epoch 20/20
60000/60000 [=====] - 4s 71us/step - loss: 0.0085 - acc: 0.9975 - val_loss: 0.0882 - v
al_acc: 0.9820

```

In [34]:

```

1  #evaluation on test data
2
3  score = model_relu.evaluate(x_test,Y_test,verbose = 1)
4  print('Loss on test data is: ',score[0])
5  print('accuracy on test data is: ',score[1])

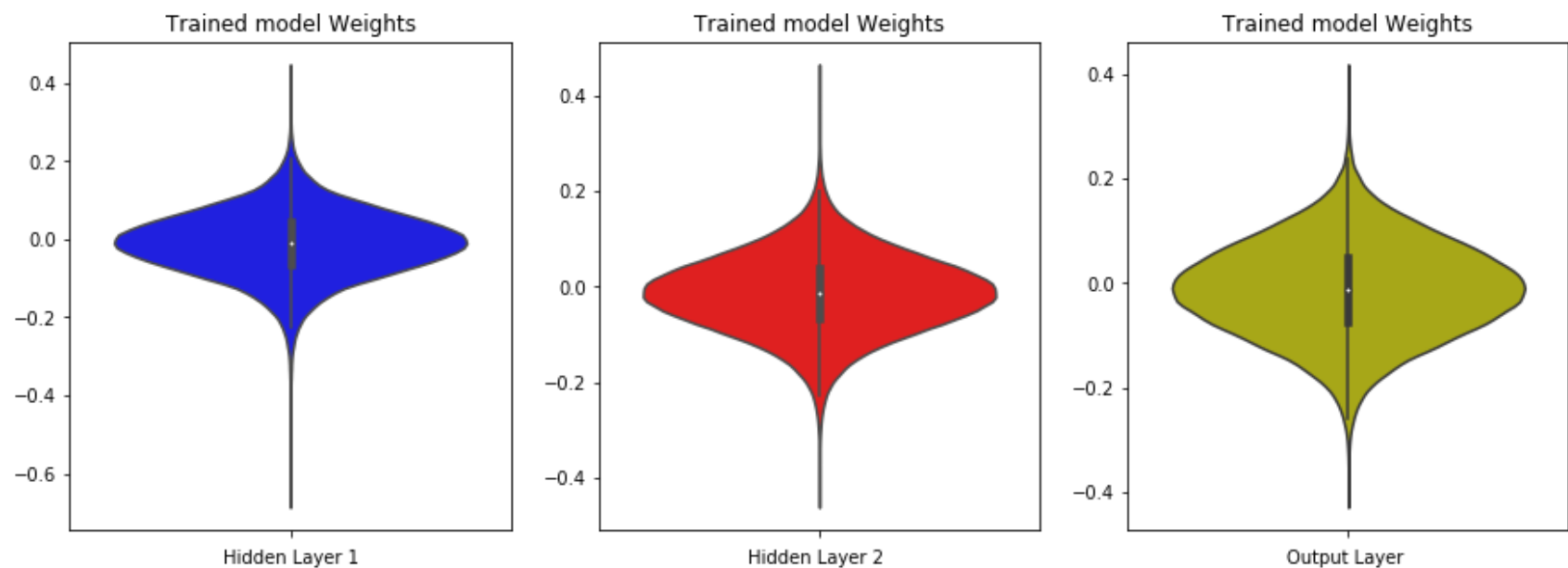
```

```

10000/10000 [=====] - 1s 71us/step
Loss on test data is:  0.08816329310913239
accuracy on test data is:  0.982

```

```
In [37]: 1 violin_plot(model_relu)
```



```
In [0]: 1 arch_2_model_1 = savetofile(history, 'arch_2_model_1')
```

## Model 2: MLP + Relu + AdamOptimizer + Dropout

In [39]:

```

1
2
3 from keras.layers import Dropout
4 model_relu_drop = Sequential()
5
6 model_relu_drop.add(Dense(1000,activation = 'relu',input_shape = (input_dim,), kernel_initializer = he_normal
7 model_relu_drop.add(Dropout(0.5))
8
9 model_relu_drop.add(Dense(500,activation = 'relu',kernel_initializer = he_normal(seed = None)))
10 model_relu_drop.add(Dropout(0.5))
11
12 model_relu_drop.add(Dense(250,activation = 'relu',kernel_initializer = he_normal(seed = None)))
13 model_relu_drop.add(Dropout(0.5))
14
15
16
17 model_relu_drop.add(Dense(output_dim,activation = 'softmax'))
18 print(model_relu_drop.summary())
19
20 model_relu_drop.compile(optimizer = 'adam',loss = 'categorical_crossentropy',metrics = ['accuracy'])
21 history = model_relu_drop.fit(x_train,Y_train,batch_size = batch_size,epochs = nb_epoch,verbose = 1,validati
22
23
24

```

Layer (type)	Output Shape	Param #
=====		
dense_17 (Dense)	(None, 1000)	785000
dropout_5 (Dropout)	(None, 1000)	0
dense_18 (Dense)	(None, 500)	500500
dropout_6 (Dropout)	(None, 500)	0
dense_19 (Dense)	(None, 250)	125250
dropout_7 (Dropout)	(None, 250)	0
dense_20 (Dense)	(None, 10)	2510

```
=====
Total params: 1,413,260
Trainable params: 1,413,260
Non-trainable params: 0
```

---

None

Train on 60000 samples, validate on 10000 samples

Epoch 1/20

60000/60000 [=====] - 6s 107us/step - loss: 0.4537 - acc: 0.8580 - val\_loss: 0.1325 - val\_acc: 0.9586

Epoch 2/20

60000/60000 [=====] - 5s 78us/step - loss: 0.1918 - acc: 0.9444 - val\_loss: 0.1045 - val\_acc: 0.9677

Epoch 3/20

60000/60000 [=====] - 5s 78us/step - loss: 0.1493 - acc: 0.9565 - val\_loss: 0.0926 - val\_acc: 0.9727

Epoch 4/20

60000/60000 [=====] - 5s 77us/step - loss: 0.1252 - acc: 0.9640 - val\_loss: 0.0826 - val\_acc: 0.9759

Epoch 5/20

60000/60000 [=====] - 5s 78us/step - loss: 0.1088 - acc: 0.9691 - val\_loss: 0.0775 - val\_acc: 0.9762

Epoch 6/20

60000/60000 [=====] - 5s 78us/step - loss: 0.1008 - acc: 0.9706 - val\_loss: 0.0667 - val\_acc: 0.9788

Epoch 7/20

60000/60000 [=====] - 5s 77us/step - loss: 0.0888 - acc: 0.9741 - val\_loss: 0.0665 - val\_acc: 0.9787

Epoch 8/20

60000/60000 [=====] - 5s 76us/step - loss: 0.0840 - acc: 0.9753 - val\_loss: 0.0698 - val\_acc: 0.9789

Epoch 9/20

60000/60000 [=====] - 5s 77us/step - loss: 0.0818 - acc: 0.9760 - val\_loss: 0.0636 - val\_acc: 0.9819

Epoch 10/20

60000/60000 [=====] - 5s 76us/step - loss: 0.0736 - acc: 0.9788 - val\_loss: 0.0615 - val\_acc: 0.9820

Epoch 11/20

60000/60000 [=====] - 5s 77us/step - loss: 0.0704 - acc: 0.9791 - val\_loss: 0.0594 - val\_acc: 0.9816

Epoch 12/20

60000/60000 [=====] - 5s 80us/step - loss: 0.0676 - acc: 0.9798 - val\_loss: 0.0598 - val\_acc: 0.9831



```

Epoch 13/20
60000/60000 [=====] - 5s 84us/step - loss: 0.0634 - acc: 0.9816 - val_loss: 0.0677 - v
al_acc: 0.9809
Epoch 14/20
60000/60000 [=====] - 5s 83us/step - loss: 0.0616 - acc: 0.9816 - val_loss: 0.0600 - v
al_acc: 0.9830
Epoch 15/20
60000/60000 [=====] - 5s 84us/step - loss: 0.0598 - acc: 0.9825 - val_loss: 0.0607 - v
al_acc: 0.9830
Epoch 16/20
60000/60000 [=====] - 5s 83us/step - loss: 0.0558 - acc: 0.9833 - val_loss: 0.0638 - v
al_acc: 0.9833
Epoch 17/20
60000/60000 [=====] - 5s 80us/step - loss: 0.0565 - acc: 0.9831 - val_loss: 0.0693 - v
al_acc: 0.9824
Epoch 18/20
60000/60000 [=====] - 5s 77us/step - loss: 0.0524 - acc: 0.9847 - val_loss: 0.0585 - v
al_acc: 0.9849
Epoch 19/20
60000/60000 [=====] - 5s 76us/step - loss: 0.0526 - acc: 0.9845 - val_loss: 0.0642 - v
al_acc: 0.9831
Epoch 20/20
60000/60000 [=====] - 5s 76us/step - loss: 0.0504 - acc: 0.9851 - val_loss: 0.0612 - v
al_acc: 0.9836

```

```

In [40]: 1 score = model_relu_drop.evaluate(x_test,Y_test,verbose = 1)
          2 print('Loss on test data is: ',score[0])
          3 print('accuracy on test data is: ',score[1])

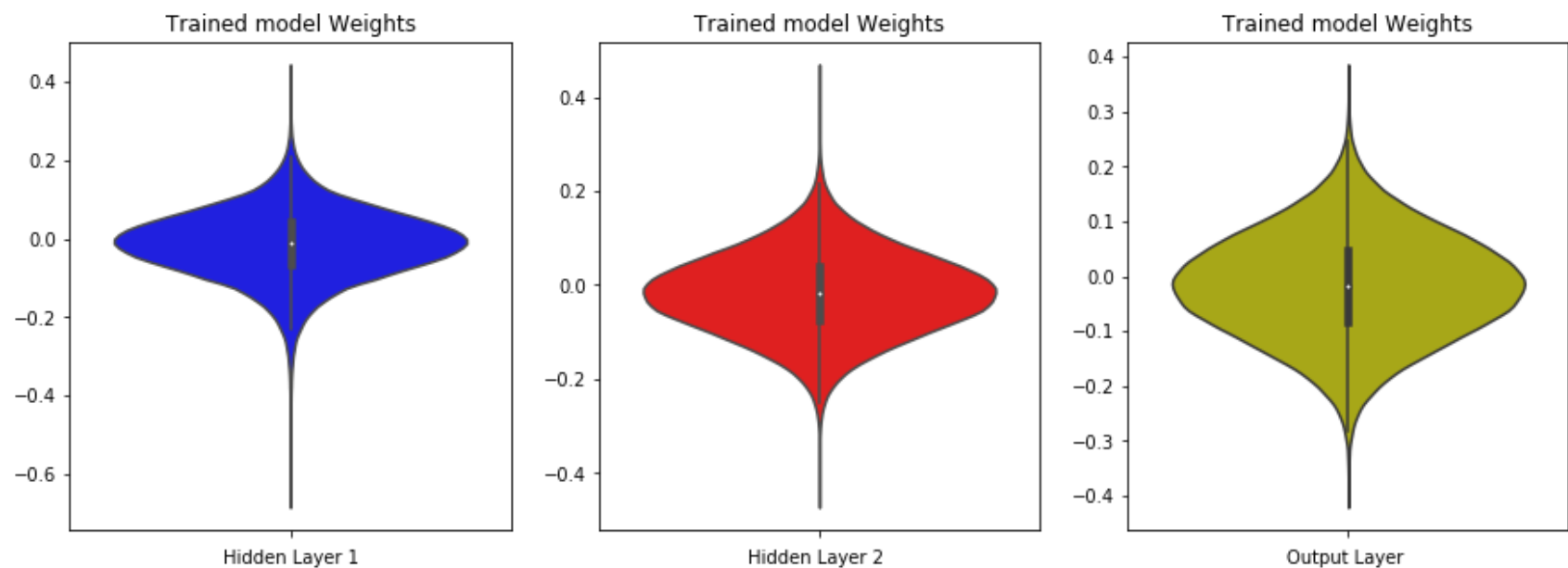
```

```

10000/10000 [=====] - 1s 69us/step
Loss on test data is: 0.061200255445798345
accuracy on test data is: 0.9836

```

```
In [41]: 1 violin_plot(model_relu_drop)
```



```
In [0]: 1 arch_2_model_2 = savetofile(history, 'arch_2_model_2')
```

**Model3 : MLP + Relu + Adamoptimizer + BatchNormalization**

```

In [43]: 1  ## Model 3
2  model_relu_batch = Sequential()
3  model_relu_batch.add(Dense(1000,activation = 'relu',input_shape = (input_dim,),kernel_initializer = he_normal
4  model_relu_batch.add(BatchNormalization())
5
6  model_relu_batch.add(Dense(500,activation = 'relu',kernel_initializer = he_normal(seed = None)))
7  model_relu_batch.add(BatchNormalization())
8
9  model_relu_batch.add(Dense(250,activation = 'relu',kernel_initializer = he_normal(seed = None)))
10 model_relu_batch.add(BatchNormalization())
11
12 model_relu_batch.add(Dense(output_dim,activation = 'softmax'))
13 print(model_relu_batch.summary())
14
15
16 model_relu_batch.compile(optimizer = 'adam',loss = 'categorical_crossentropy',metrics = ['accuracy'])
17 history = model_relu_batch.fit(x_train,Y_train,batch_size = batch_size,epochs = nb_epoch,verbose = 1,validat
18
19

```

Layer (type)	Output Shape	Param #
dense_21 (Dense)	(None, 1000)	785000
batch_normalization_5 (Batch Normalization)	(None, 1000)	4000
dense_22 (Dense)	(None, 500)	500500
batch_normalization_6 (Batch Normalization)	(None, 500)	2000
dense_23 (Dense)	(None, 250)	125250
batch_normalization_7 (Batch Normalization)	(None, 250)	1000
dense_24 (Dense)	(None, 10)	2510
Total params: 1,420,260		
Trainable params: 1,416,760		
Non-trainable params: 3,500		

None

Train on 60000 samples, validate on 10000 samples

Epoch 1/20

60000/60000 [=====] - 10s 169us/step - loss: 0.1613 - acc: 0.9502 - val\_loss: 0.0893 - val\_acc: 0.9721

Epoch 2/20

60000/60000 [=====] - 8s 129us/step - loss: 0.0654 - acc: 0.9794 - val\_loss: 0.0841 - val\_acc: 0.9728

Epoch 3/20

60000/60000 [=====] - 8s 130us/step - loss: 0.0441 - acc: 0.9862 - val\_loss: 0.0803 - val\_acc: 0.9755

Epoch 4/20

60000/60000 [=====] - 8s 129us/step - loss: 0.0356 - acc: 0.9882 - val\_loss: 0.0733 - val\_acc: 0.9767

Epoch 5/20

60000/60000 [=====] - 8s 132us/step - loss: 0.0283 - acc: 0.9907 - val\_loss: 0.0960 - val\_acc: 0.9718

Epoch 6/20

60000/60000 [=====] - 8s 135us/step - loss: 0.0272 - acc: 0.9906 - val\_loss: 0.0766 - val\_acc: 0.9778

Epoch 7/20

60000/60000 [=====] - 8s 137us/step - loss: 0.0212 - acc: 0.9927 - val\_loss: 0.0784 - val\_acc: 0.9765

Epoch 8/20

60000/60000 [=====] - 8s 137us/step - loss: 0.0202 - acc: 0.9933 - val\_loss: 0.0773 - val\_acc: 0.9794

Epoch 9/20

60000/60000 [=====] - 8s 136us/step - loss: 0.0188 - acc: 0.9939 - val\_loss: 0.0950 - val\_acc: 0.9755

Epoch 10/20

60000/60000 [=====] - 8s 138us/step - loss: 0.0167 - acc: 0.9943 - val\_loss: 0.0744 - val\_acc: 0.9794

Epoch 11/20

60000/60000 [=====] - 8s 138us/step - loss: 0.0164 - acc: 0.9945 - val\_loss: 0.0881 - val\_acc: 0.9785

Epoch 12/20

60000/60000 [=====] - 8s 135us/step - loss: 0.0164 - acc: 0.9944 - val\_loss: 0.0763 - val\_acc: 0.9805

Epoch 13/20

60000/60000 [=====] - 8s 137us/step - loss: 0.0127 - acc: 0.9957 - val\_loss: 0.0662 - val\_acc: 0.9827

Epoch 14/20

60000/60000 [=====] - 9s 143us/step - loss: 0.0106 - acc: 0.9964 - val\_loss: 0.0812 -

```

val_acc: 0.9811
Epoch 15/20
60000/60000 [=====] - 8s 141us/step - loss: 0.0120 - acc: 0.9961 - val_loss: 0.1095 -
val_acc: 0.9766
Epoch 16/20
60000/60000 [=====] - 8s 141us/step - loss: 0.0121 - acc: 0.9958 - val_loss: 0.0758 -
val_acc: 0.9821
Epoch 17/20
60000/60000 [=====] - 9s 143us/step - loss: 0.0085 - acc: 0.9972 - val_loss: 0.0858 -
val_acc: 0.9786
Epoch 18/20
60000/60000 [=====] - 9s 144us/step - loss: 0.0094 - acc: 0.9965 - val_loss: 0.0894 -
val_acc: 0.9788
Epoch 19/20
60000/60000 [=====] - 9s 144us/step - loss: 0.0113 - acc: 0.9963 - val_loss: 0.0856 -
val_acc: 0.9792
Epoch 20/20
60000/60000 [=====] - 9s 142us/step - loss: 0.0071 - acc: 0.9979 - val_loss: 0.0750 -
val_acc: 0.9837

```

```

In [44]: 1 score = model_relu_batch.evaluate(x_test,Y_test,verbose = 1)
          2 print('Loss on the test data is: ',score[0])
          3 print('Accuracy on the test data is:',score[1])

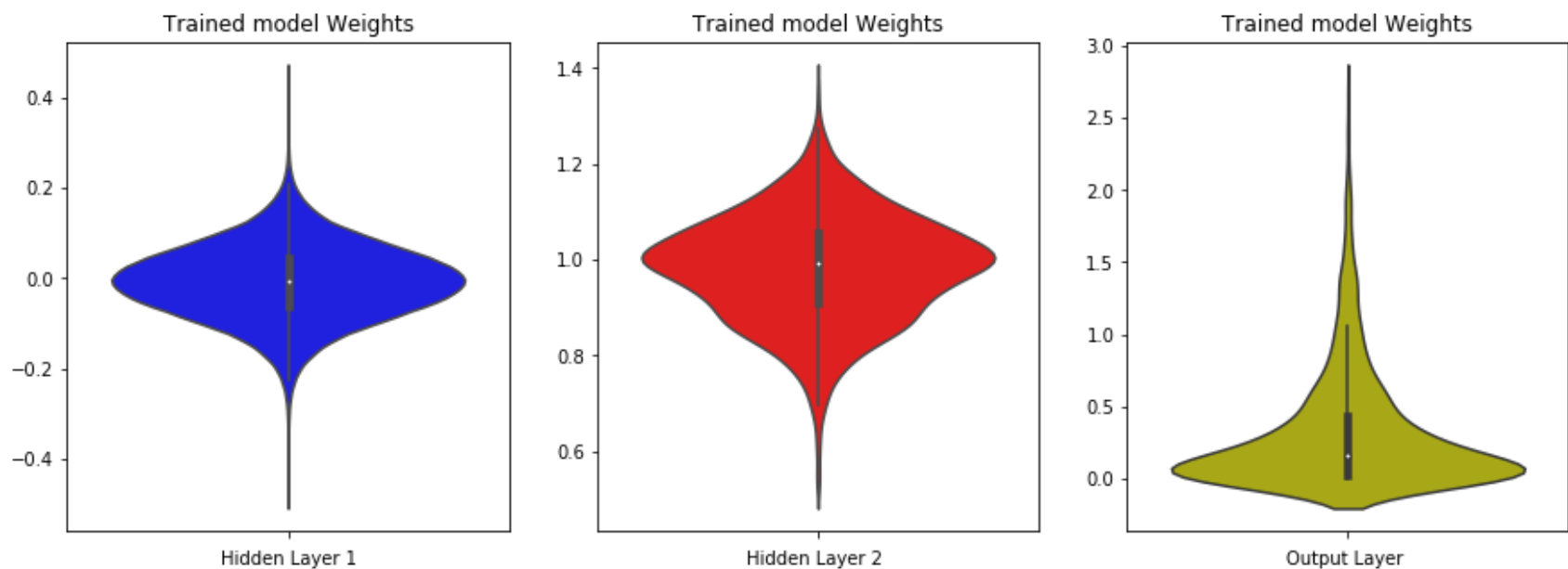
```

```

10000/10000 [=====] - 1s 100us/step
Loss on the test data is: 0.07504327980409116
Accuracy on the test data is: 0.9837

```

```
In [45]: 1 violin_plot(model_relu_batch)
```



```
In [0]: 1 arch_2_model_3 = savetofile(history, 'arch_2_model_3')
```

**Model4: MLP + Relu + Adamoptimizer + BatchNormalization + Dropout**

In [47]:

```

1  ## Model 4
2
3  model_relu_batch_drop = Sequential()
4  model_relu_batch_drop.add(Dense(1000,activation = 'relu',input_shape = (input_dim,),kernel_initializer = he_
5  model_relu_batch_drop.add(BatchNormalization())
6  model_relu_batch_drop.add(Dropout(0.5))
7
8
9  model_relu_batch_drop.add(Dense(500,activation = 'relu',kernel_initializer = he_normal(seed = None)))
10 model_relu_batch_drop.add(BatchNormalization())
11 model_relu_batch_drop.add(Dropout(0.5))
12
13
14 model_relu_batch_drop.add(Dense(250,activation = 'relu',kernel_initializer = he_normal(seed = None)))
15 model_relu_batch_drop.add(BatchNormalization())
16 model_relu_batch_drop.add(Dropout(0.5))
17
18
19 model_relu_batch_drop.add(Dense(output_dim,activation = 'softmax'))
20 print(model_relu_batch_drop.summary())
21
22 model_relu_batch_drop.compile(optimizer = 'adam',loss = 'categorical_crossentropy',metrics = ['accuracy'])
23 history = model_relu_batch_drop.fit(x_train,Y_train,batch_size = batch_size,epochs = nb_epoch,verbose = 1,va
24

```

Layer (type)	Output Shape	Param #
dense_25 (Dense)	(None, 1000)	785000
batch_normalization_8 (Batch Normalization)	(None, 1000)	4000
dropout_8 (Dropout)	(None, 1000)	0
dense_26 (Dense)	(None, 500)	500500
batch_normalization_9 (Batch Normalization)	(None, 500)	2000
dropout_9 (Dropout)	(None, 500)	0
dense_27 (Dense)	(None, 250)	125250

batch_normalization_10 (Batch Normalization)	(None, 250)	1000
dropout_10 (Dropout)	(None, 250)	0
dense_28 (Dense)	(None, 10)	2510
=====		
Total params: 1,420,260		
Trainable params: 1,416,760		
Non-trainable params: 3,500		

None

Train on 60000 samples, validate on 10000 samples

Epoch 1/20

60000/60000 [=====] - 12s 192us/step - loss: 0.4173 - acc: 0.8741 - val\_loss: 0.1345 - val\_acc: 0.9598

Epoch 2/20

60000/60000 [=====] - 8s 138us/step - loss: 0.1879 - acc: 0.9437 - val\_loss: 0.1048 - val\_acc: 0.9661

Epoch 3/20

60000/60000 [=====] - 8s 137us/step - loss: 0.1495 - acc: 0.9543 - val\_loss: 0.0883 - val\_acc: 0.9721

Epoch 4/20

60000/60000 [=====] - 8s 136us/step - loss: 0.1230 - acc: 0.9624 - val\_loss: 0.0769 - val\_acc: 0.9770

Epoch 5/20

60000/60000 [=====] - 8s 137us/step - loss: 0.1073 - acc: 0.9668 - val\_loss: 0.0709 - val\_acc: 0.9775

Epoch 6/20

60000/60000 [=====] - 8s 135us/step - loss: 0.0976 - acc: 0.9700 - val\_loss: 0.0645 - val\_acc: 0.9791

Epoch 7/20

60000/60000 [=====] - 8s 136us/step - loss: 0.0920 - acc: 0.9710 - val\_loss: 0.0658 - val\_acc: 0.9796

Epoch 8/20

60000/60000 [=====] - 8s 136us/step - loss: 0.0809 - acc: 0.9750 - val\_loss: 0.0582 - val\_acc: 0.9818

Epoch 9/20

60000/60000 [=====] - 8s 136us/step - loss: 0.0771 - acc: 0.9749 - val\_loss: 0.0539 - val\_acc: 0.9835

Epoch 10/20

60000/60000 [=====] - 8s 134us/step - loss: 0.0719 - acc: 0.9772 - val\_loss: 0.0629 - val\_acc: 0.9829



```

Epoch 11/20
60000/60000 [=====] - 8s 136us/step - loss: 0.0666 - acc: 0.9790 - val_loss: 0.0610 -
val_acc: 0.9820
Epoch 12/20
60000/60000 [=====] - 8s 135us/step - loss: 0.0657 - acc: 0.9789 - val_loss: 0.0617 -
val_acc: 0.9822
Epoch 13/20
60000/60000 [=====] - 8s 135us/step - loss: 0.0604 - acc: 0.9814 - val_loss: 0.0591 -
val_acc: 0.9829
Epoch 14/20
60000/60000 [=====] - 8s 135us/step - loss: 0.0596 - acc: 0.9809 - val_loss: 0.0558 -
val_acc: 0.9826
Epoch 15/20
60000/60000 [=====] - 8s 136us/step - loss: 0.0573 - acc: 0.9815 - val_loss: 0.0581 -
val_acc: 0.9830
Epoch 16/20
60000/60000 [=====] - 8s 136us/step - loss: 0.0569 - acc: 0.9819 - val_loss: 0.0594 -
val_acc: 0.9824
Epoch 17/20
60000/60000 [=====] - 8s 137us/step - loss: 0.0504 - acc: 0.9837 - val_loss: 0.0548 -
val_acc: 0.9843
Epoch 18/20
60000/60000 [=====] - 8s 137us/step - loss: 0.0498 - acc: 0.9842 - val_loss: 0.0566 -
val_acc: 0.9835
Epoch 19/20
60000/60000 [=====] - 8s 137us/step - loss: 0.0461 - acc: 0.9854 - val_loss: 0.0540 -
val_acc: 0.9843
Epoch 20/20
60000/60000 [=====] - 8s 135us/step - loss: 0.0447 - acc: 0.9855 - val_loss: 0.0521 -
val_acc: 0.9849

```

```

In [48]: 1 score = model_relu_batch_drop.evaluate(x_test,Y_test)
          2 print('loss on test data is:',score[0])
          3 print('accuracy on test data is',score[1])

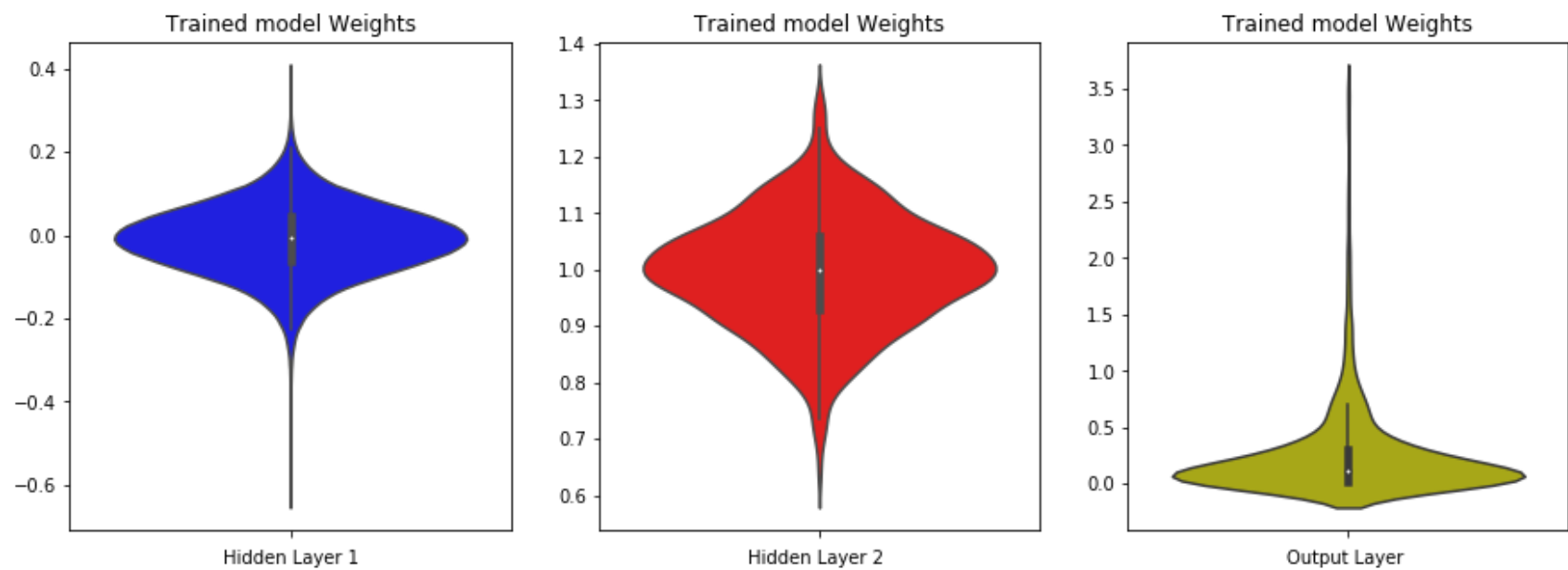
```

```

10000/10000 [=====] - 1s 95us/step
loss on test data is: 0.05211034208216879
accuracy on test data is 0.9849

```

```
In [49]: 1 violin_plot(model_relu_batch_drop)
```



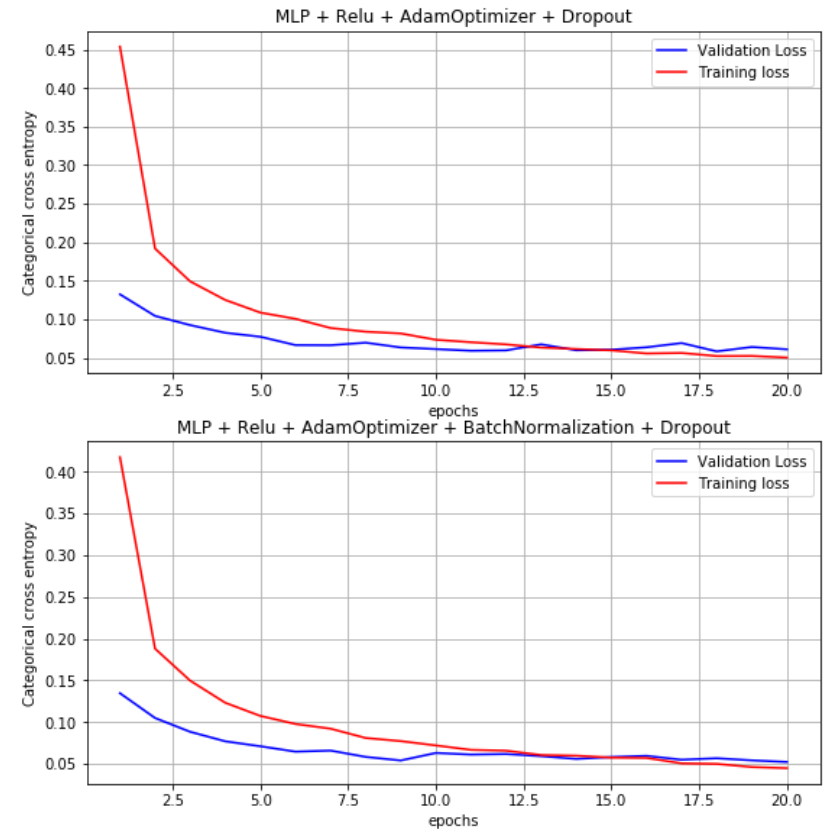
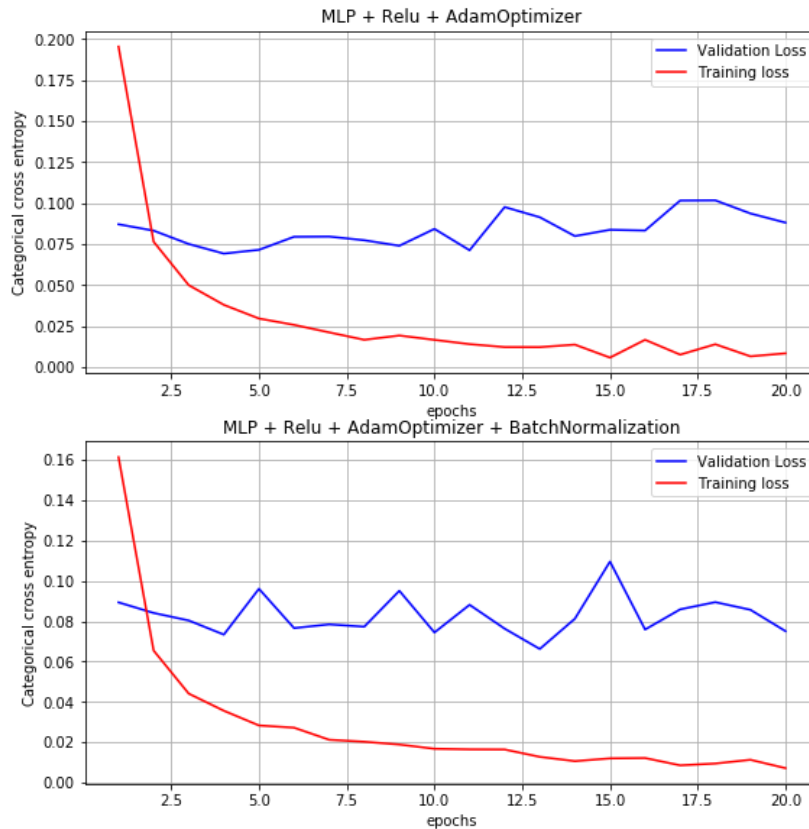
```
In [0]: 1 arch_2_model_4 = savetofile(history, 'arch_2_model_4')
```

```
In [54]: 1 #plotting for all four models
2
3 plt.figure(figsize = (20,20))
4 #plt.grid()
5 x = list(range(1,nb_epoch+1))
6
7 """MODEL 1"""
8 plt.subplot(4,2,1)
9 plt.title('MLP + Relu + AdamOptimizer')
10 plt.grid()
11 plt.plot(x,openfromfile('arch_2_model_1').history['val_loss'],color = 'b',label = 'Validation Loss')
12 plt.plot(x,openfromfile('arch_2_model_1').history['loss'],color = 'r',label = 'Training loss')
13 plt.xlabel('epochs')
14 plt.ylabel('Categorical cross entropy')
15 plt.legend()
16
17
18 """MODEL 2"""
19
20 plt.subplot(4,2,2)
21 plt.title('MLP + Relu + AdamOptimizer + Dropout')
22 plt.grid()
23 plt.plot(x,openfromfile('arch_2_model_2').history['val_loss'],color = 'b',label = 'Validation Loss')
24 plt.plot(x,openfromfile('arch_2_model_2').history['loss'],color = 'r',label = 'Training loss')
25 plt.xlabel('epochs')
26 plt.ylabel('Categorical cross entropy')
27 plt.legend()
28
29
30
31 """MODEL 3"""
32 plt.subplot(4,2,3)
33 plt.title('MLP + Relu + AdamOptimizer + BatchNormalization')
34 plt.grid()
35 plt.plot(x,openfromfile('arch_2_model_3').history['val_loss'],color = 'b',label = 'Validation Loss')
36 plt.plot(x,openfromfile('arch_2_model_3').history['loss'],color = 'r',label = 'Training loss')
37 plt.xlabel('epochs')
38 plt.ylabel('Categorical cross entropy')
39 plt.legend()
40
41
42 """MODEL 4"""
```

```

43 plt.subplot(4,2,4)
44 plt.title('MLP + Relu + AdamOptimizer + BatchNormalization + Dropout')
45 plt.grid()
46 plt.plot(x,openfromfile('arch_2_model_4').history['val_loss'],color = 'b',label = 'Validation Loss')
47 plt.plot(x,openfromfile('arch_2_model_4').history['loss'],color = 'r',label = 'Training loss')
48 plt.xlabel('epochs')
49 plt.ylabel('Categorical cross entropy')
50 plt.legend()
51 plt.show()

```



## Architecture 3: Model with 5 hidden layers

**Input(786) - relu(200) - relu(300) - relu (400) - relu(500) - relu(600) - softmax(10)**

## Model1: MLP + Relu + Adamoptimizer

```
In [66]: 1 from keras.initializers import he_normal
2
3 model_relu = Sequential()
4 model_relu.add(Dense(200, activation='relu', input_shape=(input_dim,), kernel_initializer=he_normal(seed = N
5 model_relu.add(Dense(300, activation='relu', kernel_initializer=he_normal(seed=None)))
6 model_relu.add(Dense(400, activation='relu', kernel_initializer=he_normal(seed=None)))
7 model_relu.add(Dense(500, activation='relu', kernel_initializer=he_normal(seed=None)))
8 model_relu.add(Dense(600, activation='relu', kernel_initializer=he_normal(seed=None)))
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_dat
16
```

Layer (type)	Output Shape	Param #
dense_59 (Dense)	(None, 200)	157000
dense_60 (Dense)	(None, 300)	60300
dense_61 (Dense)	(None, 400)	120400
dense_62 (Dense)	(None, 500)	200500
dense_63 (Dense)	(None, 600)	300600
dense_64 (Dense)	(None, 10)	6010

Total params: 844,810  
 Trainable params: 844,810  
 Non-trainable params: 0

None  
 Train on 60000 samples, validate on 10000 samples  
 Epoch 1/20  
 60000/60000 [=====] - 11s 187us/step - loss: 0.2383 - acc: 0.9274 - val\_loss: 0.1470 - val\_acc: 0.9552

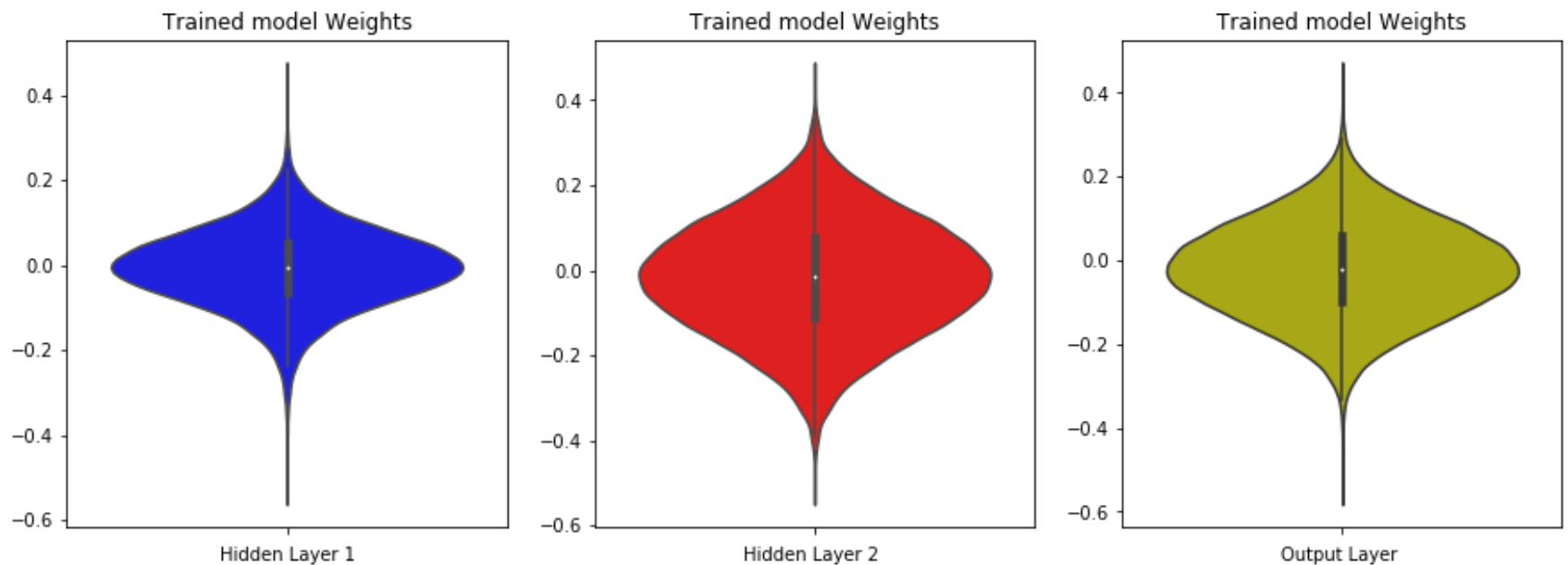
```
Epoch 2/20
60000/60000 [=====] - 5s 82us/step - loss: 0.1032 - acc: 0.9681 - val_loss: 0.1007 - val_acc: 0.9709
Epoch 3/20
60000/60000 [=====] - 5s 82us/step - loss: 0.0711 - acc: 0.9781 - val_loss: 0.0999 - val_acc: 0.9700
Epoch 4/20
60000/60000 [=====] - 5s 85us/step - loss: 0.0573 - acc: 0.9820 - val_loss: 0.0823 - val_acc: 0.9765
Epoch 5/20
60000/60000 [=====] - 5s 85us/step - loss: 0.0449 - acc: 0.9854 - val_loss: 0.0920 - val_acc: 0.9745
Epoch 6/20
60000/60000 [=====] - 5s 83us/step - loss: 0.0400 - acc: 0.9878 - val_loss: 0.1036 - val_acc: 0.9732
Epoch 7/20
60000/60000 [=====] - 5s 88us/step - loss: 0.0338 - acc: 0.9893 - val_loss: 0.1101 - val_acc: 0.9754
Epoch 8/20
60000/60000 [=====] - 5s 90us/step - loss: 0.0324 - acc: 0.9893 - val_loss: 0.1165 - val_acc: 0.9704
Epoch 9/20
60000/60000 [=====] - 5s 82us/step - loss: 0.0297 - acc: 0.9911 - val_loss: 0.0886 - val_acc: 0.9767
Epoch 10/20
60000/60000 [=====] - 5s 80us/step - loss: 0.0257 - acc: 0.9919 - val_loss: 0.0942 - val_acc: 0.9791
Epoch 11/20
60000/60000 [=====] - 5s 81us/step - loss: 0.0221 - acc: 0.9934 - val_loss: 0.1040 - val_acc: 0.9755
Epoch 12/20
60000/60000 [=====] - 5s 81us/step - loss: 0.0266 - acc: 0.9919 - val_loss: 0.1057 - val_acc: 0.9772
Epoch 13/20
60000/60000 [=====] - 5s 81us/step - loss: 0.0183 - acc: 0.9945 - val_loss: 0.1061 - val_acc: 0.9794
Epoch 14/20
60000/60000 [=====] - 5s 81us/step - loss: 0.0198 - acc: 0.9943 - val_loss: 0.0918 - val_acc: 0.9803
Epoch 15/20
60000/60000 [=====] - 5s 80us/step - loss: 0.0176 - acc: 0.9946 - val_loss: 0.0898 - val_acc: 0.9796
Epoch 16/20
```

```

60000/60000 [=====] - 5s 80us/step - loss: 0.0225 - acc: 0.9938 - val_loss: 0.0900 - v
al_acc: 0.9806
Epoch 17/20
60000/60000 [=====] - 5s 80us/step - loss: 0.0173 - acc: 0.9950 - val_loss: 0.0850 - v
al_acc: 0.9804
Epoch 18/20
60000/60000 [=====] - 5s 82us/step - loss: 0.0173 - acc: 0.9953 - val_loss: 0.0968 - v
al_acc: 0.9811
Epoch 19/20
60000/60000 [=====] - 5s 84us/step - loss: 0.0143 - acc: 0.9961 - val_loss: 0.1019 - v
al_acc: 0.9820
Epoch 20/20
60000/60000 [=====] - 5s 82us/step - loss: 0.0137 - acc: 0.9961 - val_loss: 0.0912 - v
al_acc: 0.9830

```

In [67]: 1 violin\_plot(model\_relu)



In [0]: 1 arch\_3\_model\_1 = savetofile(history, 'arch\_3\_model\_1')

## Model2: MLP + Relu + Adamoptimizer + Dropout



```

In [56]: 1  ## Model 2: mlp_relu+adam_dropout
2
3  model_relu_drop = Sequential()
4
5  model_relu_drop.add(Dense(200,activation = 'relu',input_shape = (input_dim,), kernel_initializer = he_normal
6  model_relu_drop.add(Dropout(0.5))
7
8  model_relu_drop.add(Dense(300,activation = 'relu',kernel_initializer = he_normal(seed = None)))
9  model_relu_drop.add(Dropout(0.5))
10
11 model_relu_drop.add(Dense(400,activation = 'relu',kernel_initializer = he_normal(seed = None)))
12 model_relu_drop.add(Dropout(0.5))
13
14 model_relu_drop.add(Dense(500,activation = 'relu',kernel_initializer = he_normal(seed = None)))
15 model_relu_drop.add(Dropout(0.5))
16
17 model_relu_drop.add(Dense(600,activation = 'relu',kernel_initializer = he_normal(seed = None)))
18 model_relu_drop.add(Dropout(0.5))
19
20
21
22
23 model_relu_drop.add(Dense(output_dim,activation = 'softmax'))
24 print(model_relu_drop.summary())
25
26 model_relu_drop.compile(optimizer = 'adam',loss = 'categorical_crossentropy',metrics = ['accuracy'])
27 history = model_relu_drop.fit(x_train,Y_train,batch_size = batch_size,epochs = nb_epoch,verbose = 1,validati
28
29

```

Layer (type)	Output Shape	Param #
dense_41 (Dense)	(None, 200)	157000
dropout_11 (Dropout)	(None, 200)	0
dense_42 (Dense)	(None, 300)	60300
dropout_12 (Dropout)	(None, 300)	0

dense_43 (Dense)	(None, 400)	120400
dropout_13 (Dropout)	(None, 400)	0
dense_44 (Dense)	(None, 500)	200500
dropout_14 (Dropout)	(None, 500)	0
dense_45 (Dense)	(None, 600)	300600
dropout_15 (Dropout)	(None, 600)	0
dense_46 (Dense)	(None, 10)	6010

=====

Total params: 844,810

Trainable params: 844,810

Non-trainable params: 0

None

Train on 60000 samples, validate on 10000 samples

Epoch 1/20

60000/60000 [=====] - 11s 177us/step - loss: 1.0938 - acc: 0.6332 - val\_loss: 0.2784 - val\_acc: 0.9222

Epoch 2/20

60000/60000 [=====] - 5s 82us/step - loss: 0.4213 - acc: 0.8857 - val\_loss: 0.2062 - val\_acc: 0.9431

Epoch 3/20

60000/60000 [=====] - 5s 86us/step - loss: 0.3402 - acc: 0.9121 - val\_loss: 0.1707 - val\_acc: 0.9515

Epoch 4/20

60000/60000 [=====] - 5s 86us/step - loss: 0.2892 - acc: 0.9238 - val\_loss: 0.1533 - val\_acc: 0.9591

Epoch 5/20

60000/60000 [=====] - 5s 83us/step - loss: 0.2694 - acc: 0.9303 - val\_loss: 0.1406 - val\_acc: 0.9625

Epoch 6/20

60000/60000 [=====] - 5s 84us/step - loss: 0.2491 - acc: 0.9364 - val\_loss: 0.1439 - val\_acc: 0.9627

Epoch 7/20

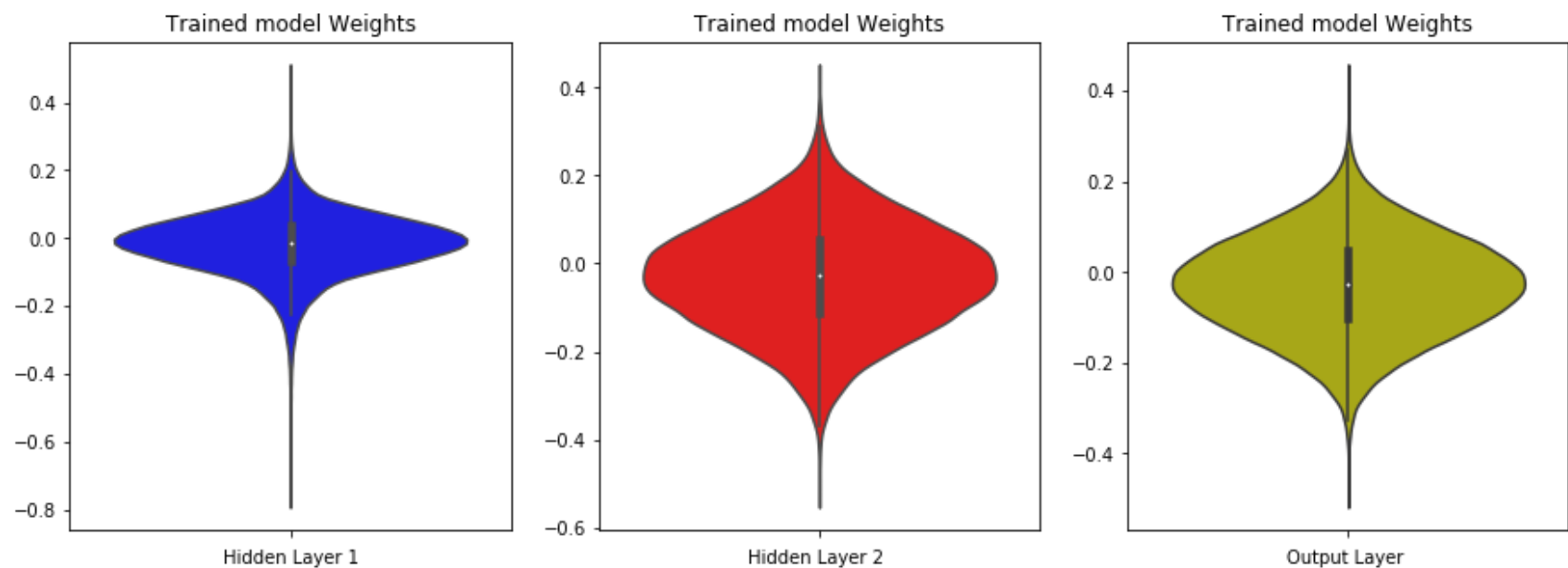
60000/60000 [=====] - 5s 85us/step - loss: 0.2335 - acc: 0.9420 - val\_loss: 0.1402 - val\_acc: 0.9624

Epoch 8/20

60000/60000 [=====] - 5s 85us/step - loss: 0.2214 - acc: 0.9427 - val\_loss: 0.1378 - val\_acc: 0.9624

```
al_acc: 0.9641
Epoch 9/20
60000/60000 [=====] - 5s 83us/step - loss: 0.2143 - acc: 0.9452 - val_loss: 0.1324 - v
al_acc: 0.9649
Epoch 10/20
60000/60000 [=====] - 5s 82us/step - loss: 0.2069 - acc: 0.9467 - val_loss: 0.1254 - v
al_acc: 0.9673
Epoch 11/20
60000/60000 [=====] - 5s 82us/step - loss: 0.1988 - acc: 0.9491 - val_loss: 0.1189 - v
al_acc: 0.9684
Epoch 12/20
60000/60000 [=====] - 5s 83us/step - loss: 0.1914 - acc: 0.9505 - val_loss: 0.1133 - v
al_acc: 0.9696
Epoch 13/20
60000/60000 [=====] - 5s 82us/step - loss: 0.1846 - acc: 0.9533 - val_loss: 0.1143 - v
al_acc: 0.9687
Epoch 14/20
60000/60000 [=====] - 5s 81us/step - loss: 0.1805 - acc: 0.9531 - val_loss: 0.1128 - v
al_acc: 0.9688
Epoch 15/20
60000/60000 [=====] - 5s 83us/step - loss: 0.1797 - acc: 0.9543 - val_loss: 0.1076 - v
al_acc: 0.9703
Epoch 16/20
60000/60000 [=====] - 5s 83us/step - loss: 0.1776 - acc: 0.9555 - val_loss: 0.1144 - v
al_acc: 0.9707
Epoch 17/20
60000/60000 [=====] - 5s 83us/step - loss: 0.1689 - acc: 0.9573 - val_loss: 0.1003 - v
al_acc: 0.9738
Epoch 18/20
60000/60000 [=====] - 5s 84us/step - loss: 0.1666 - acc: 0.9579 - val_loss: 0.1136 - v
al_acc: 0.9692
Epoch 19/20
60000/60000 [=====] - 5s 86us/step - loss: 0.1636 - acc: 0.9586 - val_loss: 0.1026 - v
al_acc: 0.9730
Epoch 20/20
60000/60000 [=====] - 5s 83us/step - loss: 0.1618 - acc: 0.9583 - val_loss: 0.1061 - v
al_acc: 0.9728
```

```
In [57]: 1 violin_plot(model_relu_drop)
```



```
In [0]: 1 arch_3_model_2 = savetofile(history, 'arch_3_model_2')
```

### Model3: MLP + Relu + Adamoptimizer + BatchNormalization

```

In [59]: 1  ## Model 3: Mlp+relu+adam+batchnormalization
2  model_relu_batch = Sequential()
3
4  model_relu_batch.add(Dense(200,activation = 'relu',input_shape = (input_dim,),kernel_initializer = he_normal
5  model_relu_batch.add(BatchNormalization())
6
7  model_relu_batch.add(Dense(300,activation = 'relu',kernel_initializer = he_normal(seed = None)))
8  model_relu_batch.add(BatchNormalization())
9
10 model_relu_batch.add(Dense(400,activation = 'relu',kernel_initializer = he_normal(seed = None)))
11 model_relu_batch.add(BatchNormalization())
12
13 #model_relu_batch = Sequential()
14 model_relu_batch.add(Dense(500,activation = 'relu',kernel_initializer = he_normal(seed = None)))
15 model_relu_batch.add(BatchNormalization())
16
17 model_relu_batch.add(Dense(600,activation = 'relu',kernel_initializer = he_normal(seed = None)))
18 model_relu_batch.add(BatchNormalization())
19
20
21
22 model_relu_batch.add(Dense(output_dim,activation = 'softmax'))
23 print(model_relu_batch.summary())
24
25 model_relu_batch.compile(optimizer = 'adam',loss = 'categorical_crossentropy',metrics = ['accuracy'])
26 history = model_relu_batch.fit(x_train,Y_train,batch_size = batch_size,epochs = nb_epoch,verbose = 1,validat
27
28

```

Layer (type)	Output Shape	Param #
dense_47 (Dense)	(None, 200)	157000
batch_normalization_11 (Batch Normalization)	(None, 200)	800
dense_48 (Dense)	(None, 300)	60300
batch_normalization_12 (Batch Normalization)	(None, 300)	1200
dense_49 (Dense)	(None, 400)	120400

batch_normalization_13 (Batch Normalization)	(None, 400)	1600
dense_50 (Dense)	(None, 500)	200500
batch_normalization_14 (Batch Normalization)	(None, 500)	2000
dense_51 (Dense)	(None, 600)	300600
batch_normalization_15 (Batch Normalization)	(None, 600)	2400
dense_52 (Dense)	(None, 10)	6010
=====		
Total params: 852,810		
Trainable params: 848,810		
Non-trainable params: 4,000		

None

Train on 60000 samples, validate on 10000 samples

Epoch 1/20

60000/60000 [=====] - 17s 276us/step - loss: 0.2225 - acc: 0.9317 - val\_loss: 0.1142 - val\_acc: 0.9664

Epoch 2/20

60000/60000 [=====] - 10s 160us/step - loss: 0.0886 - acc: 0.9721 - val\_loss: 0.1059 - val\_acc: 0.9676

Epoch 3/20

60000/60000 [=====] - 10s 160us/step - loss: 0.0662 - acc: 0.9789 - val\_loss: 0.1109 - val\_acc: 0.9679

Epoch 4/20

60000/60000 [=====] - 10s 159us/step - loss: 0.0518 - acc: 0.9835 - val\_loss: 0.0925 - val\_acc: 0.9715

Epoch 5/20

60000/60000 [=====] - 10s 170us/step - loss: 0.0441 - acc: 0.9855 - val\_loss: 0.0967 - val\_acc: 0.9730

Epoch 6/20

60000/60000 [=====] - 10s 163us/step - loss: 0.0401 - acc: 0.9872 - val\_loss: 0.1137 - val\_acc: 0.9689

Epoch 7/20

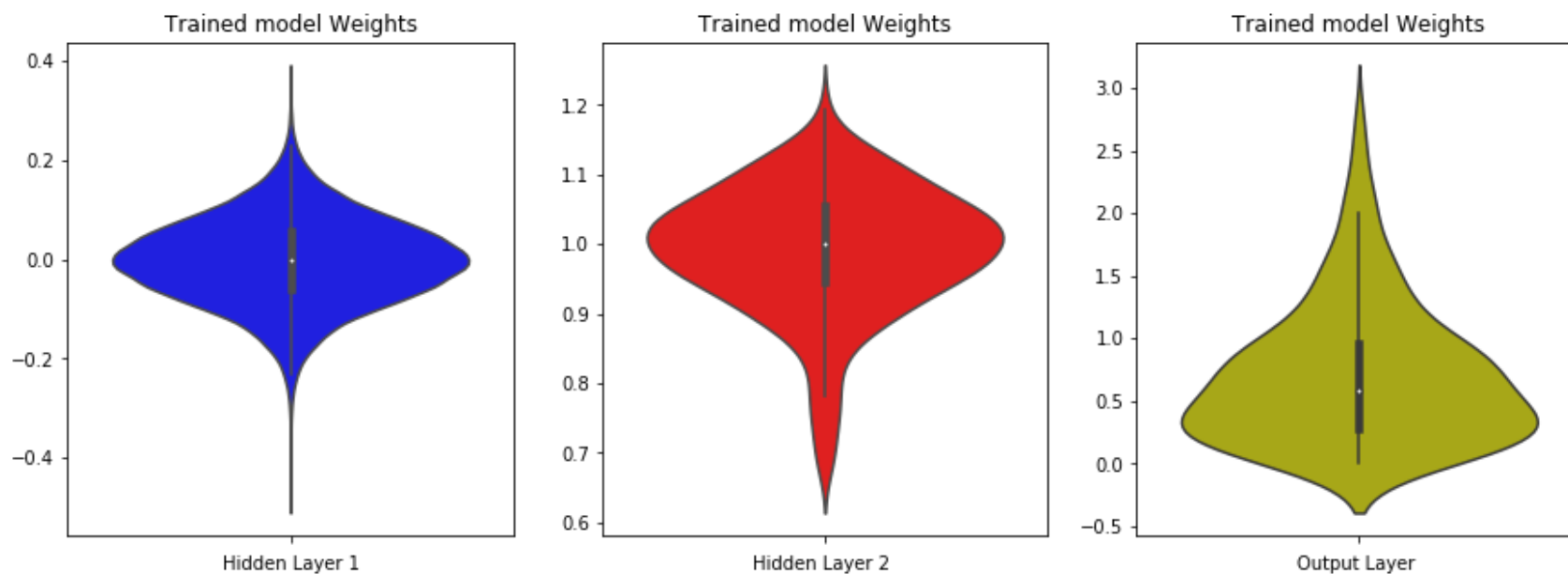
60000/60000 [=====] - 9s 158us/step - loss: 0.0348 - acc: 0.9885 - val\_loss: 0.0910 - val\_acc: 0.9771

Epoch 8/20

60000/60000 [=====] - 10s 159us/step - loss: 0.0325 - acc: 0.9890 - val\_loss: 0.0939 - val\_acc: 0.9747

```
Epoch 9/20
60000/60000 [=====] - 10s 161us/step - loss: 0.0305 - acc: 0.9896 - val_loss: 0.0874 -
val_acc: 0.9782
Epoch 10/20
60000/60000 [=====] - 10s 161us/step - loss: 0.0256 - acc: 0.9917 - val_loss: 0.1018 -
val_acc: 0.9758
Epoch 11/20
60000/60000 [=====] - 10s 161us/step - loss: 0.0306 - acc: 0.9899 - val_loss: 0.0858 -
val_acc: 0.9781
Epoch 12/20
60000/60000 [=====] - 10s 169us/step - loss: 0.0188 - acc: 0.9939 - val_loss: 0.0884 -
val_acc: 0.9793
Epoch 13/20
60000/60000 [=====] - 10s 160us/step - loss: 0.0227 - acc: 0.9926 - val_loss: 0.0938 -
val_acc: 0.9776
Epoch 14/20
60000/60000 [=====] - 10s 170us/step - loss: 0.0208 - acc: 0.9929 - val_loss: 0.1239 -
val_acc: 0.9699
Epoch 15/20
60000/60000 [=====] - 10s 164us/step - loss: 0.0198 - acc: 0.9933 - val_loss: 0.0988 -
val_acc: 0.9774
Epoch 16/20
60000/60000 [=====] - 10s 161us/step - loss: 0.0229 - acc: 0.9927 - val_loss: 0.1024 -
val_acc: 0.9754
Epoch 17/20
60000/60000 [=====] - 10s 160us/step - loss: 0.0148 - acc: 0.9952 - val_loss: 0.1036 -
val_acc: 0.9753
Epoch 18/20
60000/60000 [=====] - 9s 158us/step - loss: 0.0145 - acc: 0.9954 - val_loss: 0.1119 -
val_acc: 0.9759
Epoch 19/20
60000/60000 [=====] - 10s 161us/step - loss: 0.0200 - acc: 0.9934 - val_loss: 0.0937 -
val_acc: 0.9763
Epoch 20/20
60000/60000 [=====] - 10s 160us/step - loss: 0.0151 - acc: 0.9950 - val_loss: 0.0845 -
val_acc: 0.9808
```

```
In [60]: 1 violin_plot(model_relu_batch)
```



```
In [0]: 1 arch_3_model_3 = savetofile(history, 'arch_3_model1_3')
```

**Model4: MLP + Relu + Adamoptimizer + BtachNormalization + Dropout**



```

In [62]: 1  ## Model 4: mlp+ relu + adam+ batchNormalization + Dropout
2
3  model_relu_batch_drop = Sequential()
4  model_relu_batch_drop.add(Dense(200,activation = 'relu',input_shape = (input_dim,),kernel_initializer = he_n
5  model_relu_batch_drop.add(BatchNormalization())
6  model_relu_batch_drop.add(Dropout(0.5))
7
8
9  model_relu_batch_drop.add(Dense(300,activation = 'relu',kernel_initializer = he_normal(seed = None)))
10 model_relu_batch_drop.add(BatchNormalization())
11 model_relu_batch_drop.add(Dropout(0.5))
12
13
14 model_relu_batch_drop.add(Dense(400,activation = 'relu',kernel_initializer = he_normal(seed = None)))
15 model_relu_batch_drop.add(BatchNormalization())
16 model_relu_batch_drop.add(Dropout(0.5))
17
18
19 model_relu_batch_drop.add(Dense(500,activation = 'relu',kernel_initializer = he_normal(seed = None)))
20 model_relu_batch_drop.add(BatchNormalization())
21 model_relu_batch_drop.add(Dropout(0.5))
22
23 model_relu_batch_drop.add(Dense(600,activation = 'relu',kernel_initializer = he_normal(seed = None)))
24 model_relu_batch_drop.add(BatchNormalization())
25 model_relu_batch_drop.add(Dropout(0.5))
26
27
28 model_relu_batch_drop.add(Dense(output_dim,activation = 'softmax'))
29 print(model_relu_batch_drop.summary())
30
31 model_relu_batch_drop.compile(optimizer = 'adam',loss = 'categorical_crossentropy',metrics = ['accuracy'])
32 history = model_relu_batch_drop.fit(x_train,Y_train,batch_size = batch_size,epochs = nb_epoch,verbose = 1,va
33

```

Layer (type)	Output Shape	Param #
=====		
dense_53 (Dense)	(None, 200)	157000
-----		
batch_normalization_16 (Batc	(None, 200)	800
-----		

dropout_16 (Dropout)	(None, 200)	0
dense_54 (Dense)	(None, 300)	60300
batch_normalization_17 (Batch Normalization)	(None, 300)	1200
dropout_17 (Dropout)	(None, 300)	0
dense_55 (Dense)	(None, 400)	120400
batch_normalization_18 (Batch Normalization)	(None, 400)	1600
dropout_18 (Dropout)	(None, 400)	0
dense_56 (Dense)	(None, 500)	200500
batch_normalization_19 (Batch Normalization)	(None, 500)	2000
dropout_19 (Dropout)	(None, 500)	0
dense_57 (Dense)	(None, 600)	300600
batch_normalization_20 (Batch Normalization)	(None, 600)	2400
dropout_20 (Dropout)	(None, 600)	0
dense_58 (Dense)	(None, 10)	6010
=====		
Total params: 852,810		
Trainable params: 848,810		
Non-trainable params: 4,000		

---

None

Train on 60000 samples, validate on 10000 samples

Epoch 1/20

60000/60000 [=====] - 18s 294us/step - loss: 0.9661 - acc: 0.7062 - val\_loss: 0.2848 - val\_acc: 0.9172

Epoch 2/20

60000/60000 [=====] - 10s 170us/step - loss: 0.3900 - acc: 0.8819 - val\_loss: 0.1996 - val\_acc: 0.9399

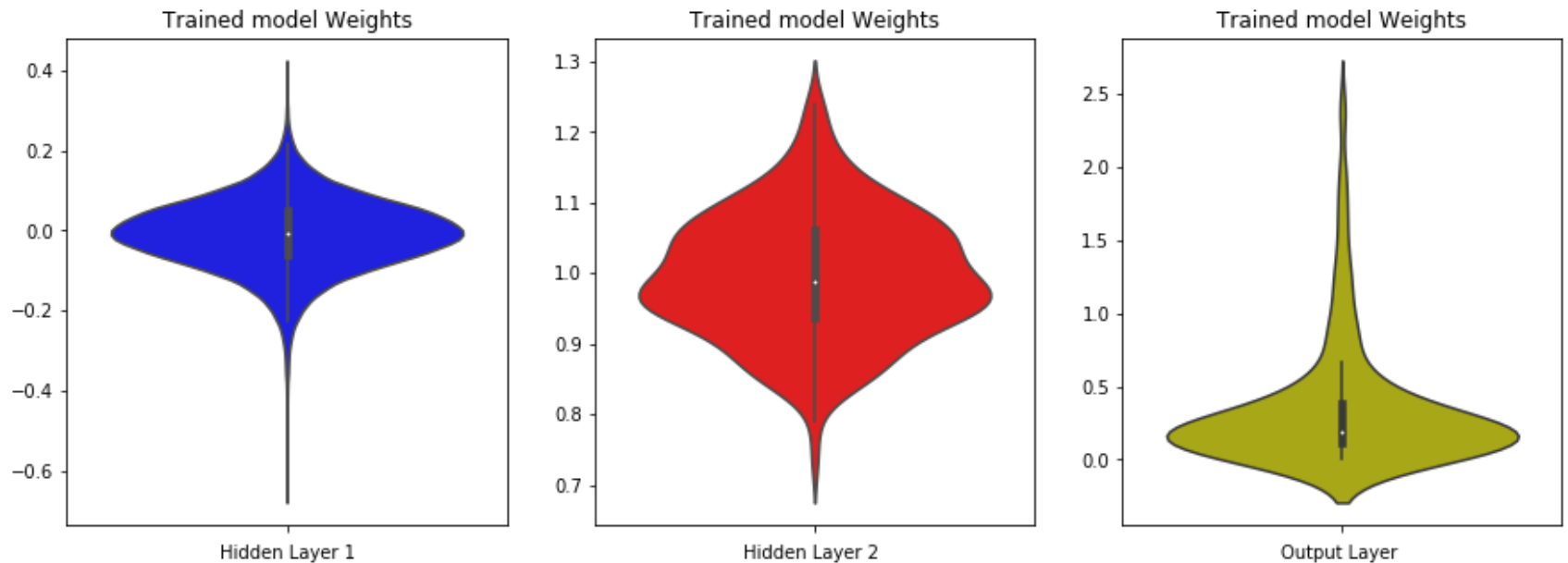
Epoch 3/20

60000/60000 [=====] - 10s 175us/step - loss: 0.3009 - acc: 0.9115 - val\_loss: 0.1443 - val\_acc: 0.9566

```
Epoch 4/20
60000/60000 [=====] - 11s 179us/step - loss: 0.2568 - acc: 0.9240 - val_loss: 0.1305 -
val_acc: 0.9607
Epoch 5/20
60000/60000 [=====] - 10s 172us/step - loss: 0.2274 - acc: 0.9333 - val_loss: 0.1209 -
val_acc: 0.9632
Epoch 6/20
60000/60000 [=====] - 10s 172us/step - loss: 0.2071 - acc: 0.9405 - val_loss: 0.1047 -
val_acc: 0.9690
Epoch 7/20
60000/60000 [=====] - 10s 170us/step - loss: 0.1903 - acc: 0.9444 - val_loss: 0.1015 -
val_acc: 0.9707
Epoch 8/20
60000/60000 [=====] - 10s 168us/step - loss: 0.1802 - acc: 0.9468 - val_loss: 0.1017 -
val_acc: 0.9687
Epoch 9/20
60000/60000 [=====] - 10s 169us/step - loss: 0.1705 - acc: 0.9505 - val_loss: 0.0984 -
val_acc: 0.9729
Epoch 10/20
60000/60000 [=====] - 10s 170us/step - loss: 0.1591 - acc: 0.9536 - val_loss: 0.0927 -
val_acc: 0.9739
Epoch 11/20
60000/60000 [=====] - 10s 170us/step - loss: 0.1496 - acc: 0.9563 - val_loss: 0.0866 -
val_acc: 0.9741
Epoch 12/20
60000/60000 [=====] - 10s 173us/step - loss: 0.1500 - acc: 0.9566 - val_loss: 0.0890 -
val_acc: 0.9745
Epoch 13/20
60000/60000 [=====] - 11s 176us/step - loss: 0.1451 - acc: 0.9584 - val_loss: 0.0843 -
val_acc: 0.9755
Epoch 14/20
60000/60000 [=====] - 10s 169us/step - loss: 0.1392 - acc: 0.9593 - val_loss: 0.0841 -
val_acc: 0.9754
Epoch 15/20
60000/60000 [=====] - 10s 168us/step - loss: 0.1321 - acc: 0.9614 - val_loss: 0.0821 -
val_acc: 0.9766
Epoch 16/20
60000/60000 [=====] - 10s 168us/step - loss: 0.1278 - acc: 0.9624 - val_loss: 0.0751 -
val_acc: 0.9784
Epoch 17/20
60000/60000 [=====] - 10s 171us/step - loss: 0.1238 - acc: 0.9637 - val_loss: 0.0764 -
val_acc: 0.9776
Epoch 18/20
```

```
60000/60000 [=====] - 10s 171us/step - loss: 0.1211 - acc: 0.9650 - val_loss: 0.0733 -  
val_acc: 0.9793  
Epoch 19/20  
60000/60000 [=====] - 10s 173us/step - loss: 0.1182 - acc: 0.9658 - val_loss: 0.0707 -  
val_acc: 0.9802  
Epoch 20/20  
60000/60000 [=====] - 11s 182us/step - loss: 0.1124 - acc: 0.9674 - val_loss: 0.0717 -  
val_acc: 0.9792
```

```
In [63]: 1 violin_plot(model_relu_batch_drop)
```



```
In [0]: 1 arch_3_model_4 = savetofile(history, 'arch_3_model_4')
```

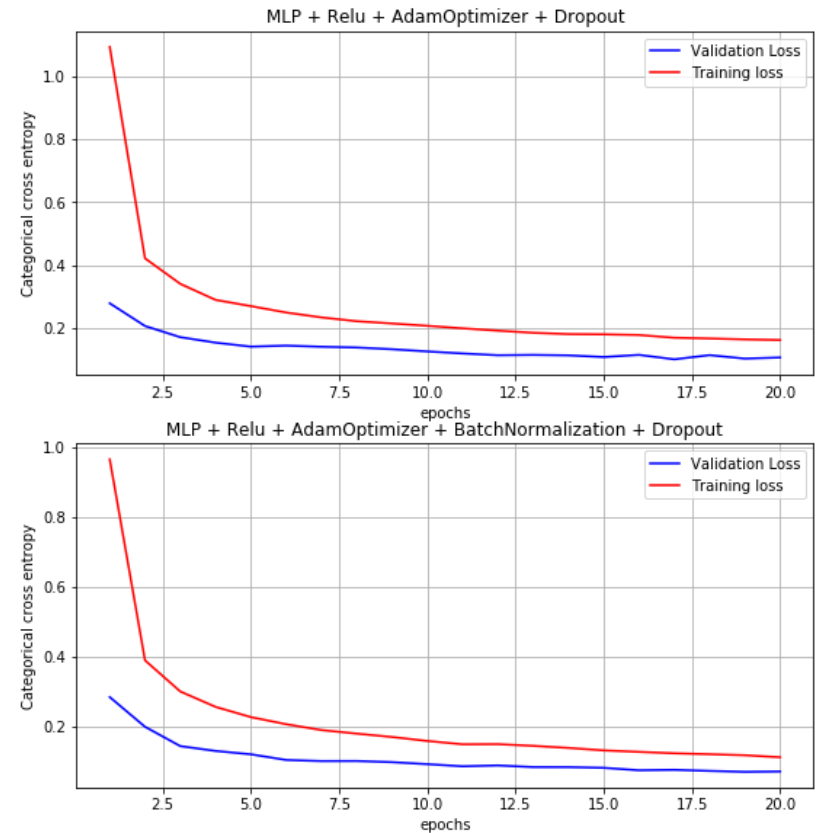
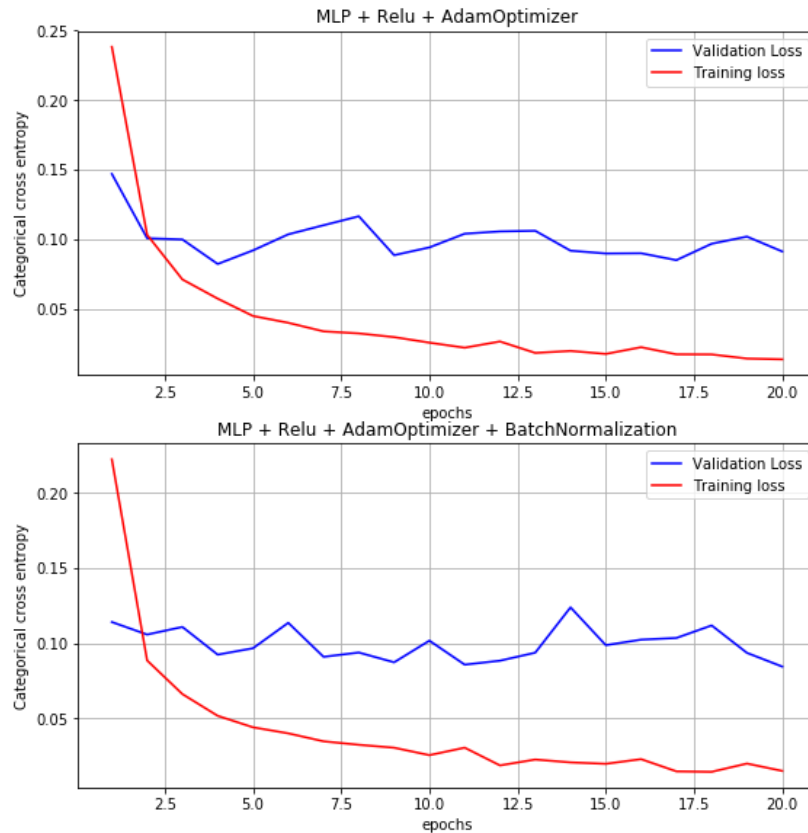
In [69]:

```
1  #plotting all the models
2
3  plt.figure(figsize = (20,20))
4  #plt.grid()
5  x = list(range(1,nb_epoch+1))
6
7  """MODEL 1"""
8  plt.subplot(4,2,1)
9  plt.title('MLP + Relu + AdamOptimizer')
10 plt.grid()
11 plt.plot(x,openfromfile('arch_3_model_1').history['val_loss'],color = 'b',label = 'Validation Loss')
12 plt.plot(x,openfromfile('arch_3_model_1').history['loss'],color = 'r',label = 'Training loss')
13 plt.xlabel('epochs')
14 plt.ylabel('Categorical cross entropy')
15 plt.legend()
16
17
18 """MODEL 2"""
19
20 plt.subplot(4,2,2)
21 plt.title('MLP + Relu + AdamOptimizer + Dropout')
22 plt.grid()
23 plt.plot(x,openfromfile('arch_3_model_2').history['val_loss'],color = 'b',label = 'Validation Loss')
24 plt.plot(x,openfromfile('arch_3_model_2').history['loss'],color = 'r',label = 'Training loss')
25 plt.xlabel('epochs')
26 plt.ylabel('Categorical cross entropy')
27 plt.legend()
28
29
30
31 """MODEL 3"""
32 plt.subplot(4,2,3)
33 plt.title('MLP + Relu + AdamOptimizer + BatchNormalization')
34 plt.grid()
35 plt.plot(x,openfromfile('arch_3_model1_3').history['val_loss'],color = 'b',label = 'Validation Loss')
36 plt.plot(x,openfromfile('arch_3_model1_3').history['loss'],color = 'r',label = 'Training loss')
37 plt.xlabel('epochs')
38 plt.ylabel('Categorical cross entropy')
39 plt.legend()
40
41
42 """MODEL 4"""
```

```

43 plt.subplot(4,2,4)
44 plt.title('MLP + Relu + AdamOptimizer + BatchNormalization + Dropout')
45 plt.grid()
46 plt.plot(x,openfromfile('arch_3_model_4').history['val_loss'],color = 'b',label = 'Validation Loss')
47 plt.plot(x,openfromfile('arch_3_model_4').history['loss'],color = 'r',label = 'Training loss')
48 plt.xlabel('epochs')
49 plt.ylabel('Categorical cross entropy')
50 plt.legend()
51 plt.show()

```



## PROCEDURE:

Following steps were followed:

- Data is imported and one hot encoded for each of the classes.

- Primarily we are considering 3 different neural network architecture here:
  - MLP with 2 hidden layers
  - MLP with 3 hidden layers
  - MLP with 5 hidden layers
- In each of the architecture we have tried 4 different for understanding the intricate working of the model and how to avoid overfitting and underfitting of the data.
  - Simple MLP
  - MLP + dropout with dropout rate = 0.5
  - MLP with Batch Normalization
  - MLP with Batch Normalization and Dropout(dropout rate = 0.5)
- After implementing each of the 4 techniques in each architecture we plot the violin plots to see the distribution of weights that we get after the implementation of optimization Algorithm.
- Finally we plot the graphs of loss vs epochs in each architecture to see how regularization is affected by adding different layers in the model.

## Conclusion

In [70]:

```

1
2
3 from prettytable import PrettyTable
4
5 table_arch1 = PrettyTable()
6 models = ['MLP + relu + adamoptimizer', 'MLP + relu + adamoptimizer + dropout', 'MLP + relu + adamoptimizer +
7 tr_loss = ['0.005', '0.0480', '0.0074', '0.0491']
8 tr_acc = ['99.82', '98.47', '99.72', '98.38']
9 te_loss = ['0.101', '0.0634', '0.0768', '0.054']
10 te_acc = ['98.02', '98.28', '98.16', '98.31']
11
12 table_arch1.add_column('Model', models)
13 table_arch1.add_column('trainig loss', tr_loss)
14 table_arch1.add_column('Training Accuracy(%)', tr_acc)
15 table_arch1.add_column('Test loss', te_loss)
16 table_arch1.add_column('Test_Accuracy(%)', te_acc)
17 print('\t\t\t\t Architecture: Input(784)-Relu(512)-Relu(256)-SoftMax(10)')
18 print(table_arch1)
19 print('\n\n\n')
20
21 table_arch2 = PrettyTable()
22 models = ['MLP + relu + adamoptimizer', 'MLP + relu + adamoptimizer + dropout', 'MLP + relu + adamoptimizer +
23 tr_loss = ['0.0052', '0.0507', '0.0002', '0.0462']
24 tr_acc = ['99.84', '98.48', '99.72', '98.53']
25 te_loss = ['0.0935', '0.0676', '0.0885', '0.0542']
26 te_acc = ['98.01', '98.36', '98.03', '98.47']
27
28 table_arch2.add_column('Model', models)
29 table_arch2.add_column('trainig loss', tr_loss)
30 table_arch2.add_column('Training Accuracy(%)', tr_acc)
31 table_arch2.add_column('Test loss', te_loss)
32 table_arch2.add_column('Test_Accuracy(%)', te_acc)
33 print('\t\t\t\t Architecture: Input(784)-Relu(1000)-Relu(500)-Relu(250)-SoftMax(10)')
34 print(table_arch2)
35 print('\n\n\n')
36
37
38
39 table_arch3 = PrettyTable()
40 models = ['MLP + relu + adamoptimizer', 'MLP + relu + adamoptimizer + dropout', 'MLP + relu + adamoptimizer +
41 tr_loss = ['0.0137', '0.1654', '0.0141', '0.114']
42 tr_acc = ['99.60', '95.75', '99.57', '96.64']

```



```

43 te_loss = ['0.0935', '0.1105', '0.0847', '0.0784']
44 te_acc = ['98.15', '97.21', '98.05', '97.83']
45
46 table_arch3.add_column('Model', models)
47 table_arch3.add_column('trainig loss', tr_loss)
48 table_arch3.add_column('Training Accuracy(%)', tr_acc)
49 table_arch3.add_column('Test loss', te_loss)
50 table_arch3.add_column('Test_Accuracy(%)', te_acc)
51 print('\t\t\t\t\t Architecture: Input(784)-Relu(200)-Relu(300)-Relu(400)-Relu(500)-Relu(600)-SoftMax(10)')
52 print(table_arch3)

```

Architecture: Input(784)-Relu(512)-Relu(256)-SoftMax(10)

-----+					
-----+					
Model		trainig loss		Training Accuracy(%)	
Test_Accuracy(%)				Test loss	
-----+					
-----+					
MLP + relu + adamoptimizer		0.005		99.82	0.101
98.02					
MLP + relu + adamoptimizer + dropout		0.0480		98.47	0.0634
98.28					
MLP + relu + adamoptimizer + BatchNormalization		0.0074		99.72	0.0768
98.16					
MLP + relu + adamoptimizer + BatchNormalization + Dropout		0.0491		98.38	0.054
98.31					
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Architecture: Input(784)-Relu(1000)-Relu(500)-Relu(250)-SoftMax(10)

Model		trainig loss	Training Accuracy(%)	Test loss
Test_Accuracy(%)				
98.01	MLP + relu + adamoptimizer	0.0052	99.84	0.0935
	MLP + relu + adamoptimizer + dropout	0.0507	98.48	0.0676

[illegible]

Architecture: Input(784)-Relu(200)-Relu(300)-Relu(400)-Relu(500)-Relu(600)-Softmax				
tMax(10)				
+-----+-----+-----+-----+				
-----+				
		Model	trainig loss	Training Accuracy(%)
Test_Accuracy(%)				Test loss
+-----+-----+-----+-----+				
-----+				
		MLP + relu + adamoptimizer	0.0137	99.60
98.15				0.0935
		MLP + relu + adamoptimizer + dropout	0.1654	95.75
97.21				0.1105
		MLP + relu + adamoptimizer + BatchNormalization	0.0141	99.57
98.05				0.0847
		MLP + relu + adamoptimizer + BatchNormalization + Dropout	0.114	96.64
97.83				0.0784
+-----+-----+-----+-----+				
-----+				