Apply different Architectures on MNIST dataset using Keras

```
import warnings
warnings.filterwarnings("ignore")
# if you keras is not using tensorflow as backend set "KERAS_BACKEND=tensorflow" use this com
from keras.utils import np_utils
from keras.datasets import mnist
import seaborn as sns
from keras.initializers import RandomNormal
#from keras.utils.visualize_util import to_graph
from keras.models import Sequential
#to_graph(Sequential())
```

READING DATA

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


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

```
Downloading data from https://s3.amazonaws.com/img-datasets/mnist.npz
11493376/11490434 [==============================] - 164s 14us/step
```

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

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

```
# if you observe the input shape its 2 dimensional vector
# for each image we have a (28*28) vector
```

```
# for each image we have a (28*28) vector
# we will convert the (28*28) vector into single dimensional vector of 1 * 784
X_train = X_train.reshape(X_train.shape[0], X_train.shape[1]*X_train.shape[2])
X_test = X_test.reshape(X_test.shape[0], X_test.shape[1]*X_test.shape[2])


# after converting the input images from 3d to 2d vectors
print("Number of training examples :", X_train.shape[0], "and each image is of shape(%d)"%(X_
print("Number of training examples :", X_test.shape[0], "and each image is of shape (%d)"%(X_
```

```
Number of training examples : 60000 and each image is of shape(784)
Number of training examples : 10000 and each image is of shape (784)
```

```
# if we observe the above matrix each cell is having a value between 0-255
# before we move to apply machine learning algorithms lets try to normalize the data
# X => (X - Xmin)/(Xmax-Xmin) = X/255
X_train = X_train/255
X_test = X_test/255


# here we are having a class number for each image
print("Class label of first image :", y_train[0])
# lets convert this into a 10 dimensional vector
# ex: consider an image is 5 convert it into 5 => [0, 0, 0, 0, 0, 1, 0, 0, 0, 0]
# this conversion needed for MLPs
Y_train = np_utils.to_categorical(y_train, 10)
Y_test = np_utils.to_categorical(y_test, 10)

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

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

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

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

```
784
```

Model 1 -- with 2 Hidden layers

1. MLP + ReLU + adam

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

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

model_relu = Sequential()
model_relu.add(Dense(610, activation='relu', input_shape=(input_dim,), kernel_initializer=Ran
model_relu.add(Dense(325, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev
model_relu.add(Dense(output_dim, activation='softmax'))
model_relu.summary()
```

```
WARNING:tensorflow:From C:\anaconda\lib\site-packages\tensorflow\python\framework\op_def
Instructions for updating:
Colocations handled automatically by placer.
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_1 (Dense)              (None, 610)               478850
_________________________________________________________________
dense_2 (Dense)              (None, 325)               198575
_________________________________________________________________
dense_3 (Dense)              (None, 10)                3260
=================================================================
Total params: 680,685
Trainable params: 680,685
Non-trainable params: 0
_________________________________________________________________
```

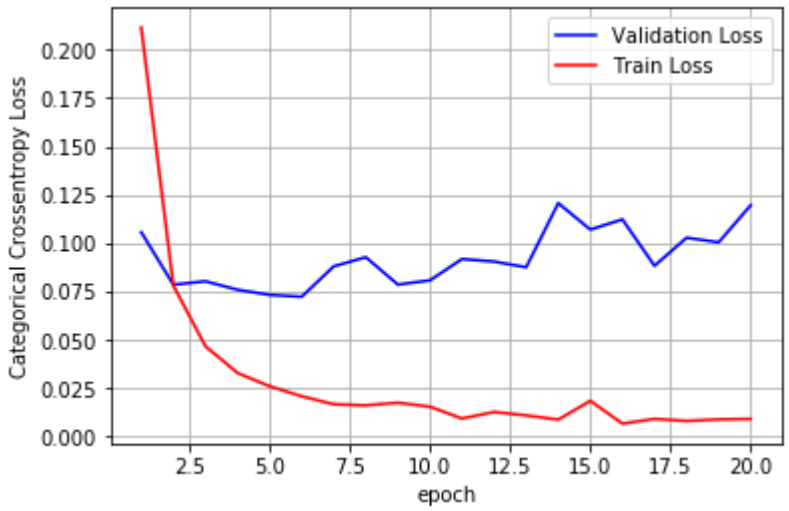
```
model_relu.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
history = model_relu.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1,
```

```
WARNING:tensorflow:From C:\anaconda\lib\site-packages\tensorflow\python\ops\math_ops.py:
Instructions for updating:
Use tf.cast instead.
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 19s 322us/step - loss: 0.2113 - acc: 0.93
Epoch 2/20
60000/60000 [==============================] - 17s 275us/step - loss: 0.0781 - acc: 0.97
Epoch 3/20
60000/60000 [==============================] - 17s 276us/step - loss: 0.0468 - acc: 0.98
Epoch 4/20
60000/60000 [==============================] - 16s 266us/step - loss: 0.0330 - acc: 0.98
Epoch 5/20
60000/60000 [==============================] - 16s 265us/step - loss: 0.0261 - acc: 0.99
Epoch 6/20
60000/60000 [==============================] - 16s 274us/step - loss: 0.0209 - acc: 0.99
Epoch 7/20
60000/60000 [==============================] - 17s 275us/step - loss: 0.0168 - acc: 0.99
Epoch 8/20
60000/60000 [==============================] - 13s 215us/step - loss: 0.0162 - acc: 0.99
Epoch 9/20
60000/60000 [==============================] - 13s 218us/step - loss: 0.0176 - acc: 0.99
Epoch 10/20
60000/60000 [==============================] - 13s 214us/step - loss: 0.0155 - acc: 0.99
Epoch 11/20
60000/60000 [==============================] - 13s 212us/step - loss: 0.0094 - acc: 0.99
Epoch 12/20
60000/60000 [==============================] - 13s 215us/step - loss: 0.0128 - acc: 0.99
Epoch 13/20
60000/60000 [==============================] - 13s 213us/step - loss: 0.0110 - acc: 0.99
Epoch 14/20
60000/60000 [==============================] - 13s 210us/step - loss: 0.0089 - acc: 0.99
Epoch 15/20
60000/60000 [==============================] - 13s 212us/step - loss: 0.0186 - acc: 0.99
Epoch 16/20
60000/60000 [==============================] - 13s 212us/step - loss: 0.0068 - acc: 0.99
Epoch 17/20
60000/60000 [==============================] - 13s 215us/step - loss: 0.0093 - acc: 0.99
Epoch 18/20
60000/60000 [==============================] - 13s 213us/step - loss: 0.0082 - acc: 0.99
Epoch 19/20
60000/60000 [==============================] - 13s 209us/step - loss: 0.0090 - acc: 0.99
Epoch 20/20
60000/60000 [==============================] - 13s 209us/step - loss: 0.0092 - acc: 0.99
```

```
#Evaluate your model with accuracy and plot of (NUmber of epoches VS train_and_val_loss)
#Train accuracy
score = model_relu.evaluate(X_train, Y_train, verbose=0)
print('Train score:', score[0])
print('Train accuracy:', score[1]*100)
print('\n********************** *********************\n')
#test accuracy
score = model_relu.evaluate(X_test, Y_test, verbose=0)
```

```
print('Test score:', score[0])
print('Test accuracy:', score[1]*100)

fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')
# list of epoch numbers
x = list(range(1,nb_epoch+1))
# print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=
# we will get val_loss and val_acc only when you pass the paramter validation_data
# val_loss : validation loss
# val_acc : validation accuracy
# loss : training loss
# acc : train accuracy
# for each key in histrory.histrory we will have a list of length equal to number of epochs
vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
```

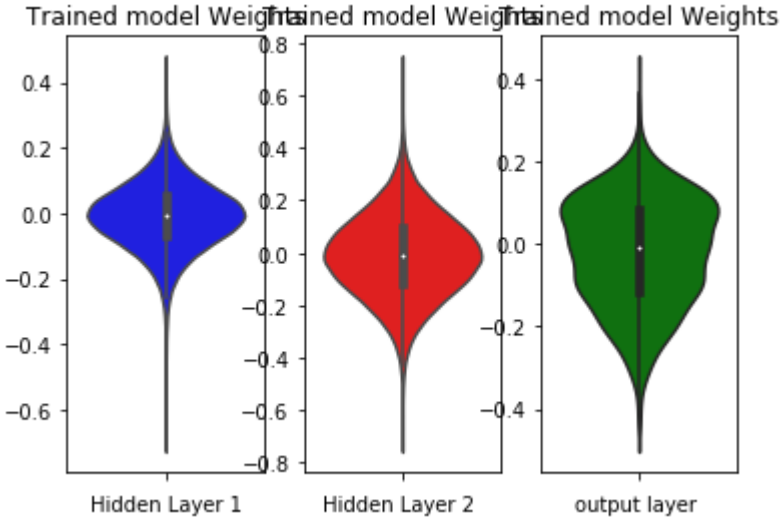
```
Train score: 0.01175171572082836
Train accuracy: 99.61166666666666

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

Test score: 0.11959466045504177
Test accuracy: 97.82
```




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

```
out_w = w_after[4].flatten().reshape(-1,1)
fig = plt.figure()
plt.title("Weight matrices after model trained")
plt.subplot(1, 3, 1)
plt.title("Trained model Weights")

ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')
plt.subplot(1, 3, 2)
plt.title("Trained model Weights")

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

ax = sns.violinplot(y=out_w, color='g')
plt.xlabel('output layer ')
```

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



2. MLP + ReLU + adam + batch__normalization

```
from keras.layers.normalization import BatchNormalization
model_batch = Sequential()
model_batch.add(Dense(610, activation='relu', input_shape=(input_dim,), kernel_initializer=Ra
model_batch.add(BatchNormalization())
model_batch.add(Dense(325, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stdde
model_batch.add(BatchNormalization())
model_batch.add(Dense(output_dim, activation='softmax'))
model_batch.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_4 (Dense)              (None, 610)               478850
_________________________________________________________________
batch_normalization_1 (Batch (None, 610)               2440
_________________________________________________________________
dense_5 (Dense)              (None, 325)               198575
_________________________________________________________________
batch_normalization_2 (Batch (None, 325)               1300
_________________________________________________________________
dense_6 (Dense)              (None, 10)                3260
=================================================================
Total params: 684,425
Trainable params: 682,555
Non-trainable params: 1,870
_________________________________________________________________
```

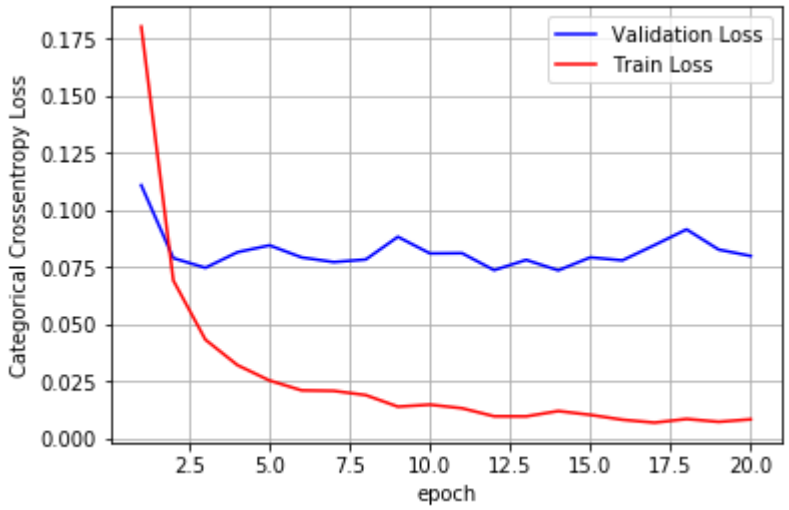
```
model_batch.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
history = model_batch.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 19s 314us/step - loss: 0.1804 - acc: 0.94
Epoch 2/20
60000/60000 [==============================] - 15s 256us/step - loss: 0.0691 - acc: 0.97
Epoch 3/20
60000/60000 [==============================] - 15s 258us/step - loss: 0.0432 - acc: 0.98
Epoch 4/20
60000/60000 [==============================] - 17s 285us/step - loss: 0.0320 - acc: 0.99
Epoch 5/20
60000/60000 [==============================] - 15s 249us/step - loss: 0.0253 - acc: 0.99
Epoch 6/20
60000/60000 [==============================] - 15s 249us/step - loss: 0.0210 - acc: 0.99
Epoch 7/20
60000/60000 [==============================] - 15s 254us/step - loss: 0.0208 - acc: 0.99
Epoch 8/20
60000/60000 [==============================] - 15s 251us/step - loss: 0.0189 - acc: 0.99
Epoch 9/20
60000/60000 [==============================] - 15s 247us/step - loss: 0.0138 - acc: 0.99
Epoch 10/20
60000/60000 [==============================] - 15s 248us/step - loss: 0.0147 - acc: 0.99
Epoch 11/20
60000/60000 [==============================] - 15s 250us/step - loss: 0.0131 - acc: 0.99
Epoch 12/20
60000/60000 [==============================] - 17s 275us/step - loss: 0.0096 - acc: 0.99
Epoch 13/20
60000/60000 [==============================] - 15s 250us/step - loss: 0.0096 - acc: 0.99
Epoch 14/20
60000/60000 [==============================] - 15s 250us/step - loss: 0.0119 - acc: 0.99
Epoch 15/20
60000/60000 [==============================] - 15s 255us/step - loss: 0.0102 - acc: 0.99
Epoch 16/20
60000/60000 [==============================] - 15s 249us/step - loss: 0.0081 - acc: 0.99
Epoch 17/20
60000/60000 [==============================] - 15s 250us/step - loss: 0.0068 - acc: 0.99
Epoch 18/20
60000/60000 [==============================] - 15s 246us/step - loss: 0.0084 - acc: 0.99
Epoch 19/20
60000/60000 [==============================] - 15s 249us/step - loss: 0.0072 - acc: 0.99
Epoch 20/20
60000/60000 [==============================] - 15s 246us/step - loss: 0.0083 - acc: 0.99
```

```
#Evaluate your model with accuracy and plot of (NUmber of epoches VS train_and_val_loss)
#Train accuracy
score = model_batch.evaluate(X_train, Y_train, verbose=0)
print('Train score:', score[0])
print('Train accuracy:', score[1]*100)
print('\n********************** *********************\n')
#test accuracy
score = model_batch.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1]*100)
fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')
```

```
# list of epoch numbers
x = list(range(1,nb_epoch+1))
# print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=
# we will get val_loss and val_acc only when you pass the paramter validation_data
# val_loss : validation loss
# val_acc : validation accuracy
# loss : training loss
# acc : train accuracy
# for each key in histrory.histrory we will have a list of length equal to number of epochs
vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
```

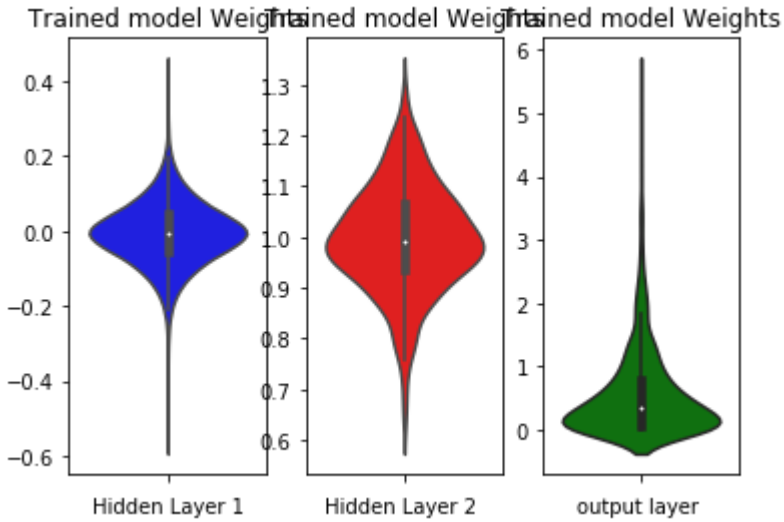
```
Train score: 0.0036005233980133805
Train accuracy: 99.88333333333334

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

Test score: 0.07985942602099326
Test accuracy: 98.2
```




```
# Weights after trainning
# 1 2 3
# input->h1->h2->output
w_after = model_batch.get_weights()
# if 2 hidden layer then
# w_after[0]is the inpupt layer weights w_after[1]is the input layer bias weights input to hi
# w_after[2]is the hidde layer weights w_after[3]is the hidde layer bias weights hidden 1 to
# w_after[4]is the hidde layer weights w_after[5]is the hidde layer bias weights hidden 2 to
h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
out_w = w_after[4].flatten().reshape(-1,1)
fig = plt.figure()
plt.title("Weight matrices after model trained")

plt.subplot(1, 3, 1)
```

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

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

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

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



3. MLP + ReLU + adam + dropout

```
# https://stackoverflow.com/questions/34716454/where-do-i-call-the-batchnormalization-functio
from keras.layers import Dropout
model_drop = Sequential()
model_drop.add(Dense(610, activation='relu', input_shape=(input_dim,), kernel_initializer=Ran
#model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))
model_drop.add(Dense(325, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev
#model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))
model_drop.add(Dense(output_dim, activation='softmax'))
model_drop.summary()
```

```
WARNING:tensorflow:From C:\anaconda\lib\site-packages\keras\backend\tensorflow_backend.p
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_7 (Dense)              (None, 610)               478850
_________________________________________________________________
dropout_1 (Dropout)          (None, 610)               0
_________________________________________________________________
dense_8 (Dense)              (None, 325)               198575
_________________________________________________________________
dropout_2 (Dropout)          (None, 325)               0
_________________________________________________________________
dense_9 (Dense)              (None, 10)                3260
=================================================================
Total params: 680,685
Trainable params: 680,685
Non-trainable params: 0
_________________________________________________________________
```

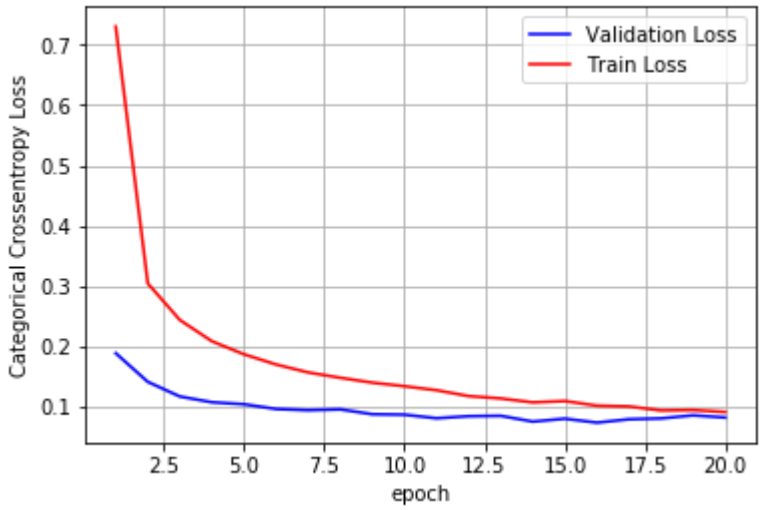
```
model_drop.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=20, verbose=1, valid
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 17s 285us/step - loss: 0.7305 - acc: 0.81
Epoch 2/20
60000/60000 [==============================] - 14s 232us/step - loss: 0.3038 - acc: 0.91
Epoch 3/20
60000/60000 [==============================] - 14s 231us/step - loss: 0.2430 - acc: 0.92
Epoch 4/20
60000/60000 [==============================] - 14s 231us/step - loss: 0.2077 - acc: 0.93
Epoch 5/20
60000/60000 [==============================] - 14s 233us/step - loss: 0.1861 - acc: 0.94
Epoch 6/20
60000/60000 [==============================] - 14s 233us/step - loss: 0.1691 - acc: 0.95
Epoch 7/20
60000/60000 [==============================] - 15s 250us/step - loss: 0.1559 - acc: 0.95
Epoch 8/20
60000/60000 [==============================] - 14s 241us/step - loss: 0.1471 - acc: 0.95
Epoch 9/20
60000/60000 [==============================] - 14s 234us/step - loss: 0.1390 - acc: 0.96
Epoch 10/20
60000/60000 [==============================] - 14s 235us/step - loss: 0.1331 - acc: 0.96
Epoch 11/20
60000/60000 [==============================] - 14s 235us/step - loss: 0.1264 - acc: 0.96
Epoch 12/20
60000/60000 [==============================] - 14s 235us/step - loss: 0.1167 - acc: 0.96
Epoch 13/20
60000/60000 [==============================] - 14s 239us/step - loss: 0.1127 - acc: 0.96
Epoch 14/20
60000/60000 [==============================] - 15s 245us/step - loss: 0.1062 - acc: 0.96
Epoch 15/20
60000/60000 [==============================] - 14s 237us/step - loss: 0.1084 - acc: 0.96
Epoch 16/20
60000/60000 [==============================] - 14s 234us/step - loss: 0.1008 - acc: 0.97
Epoch 17/20
60000/60000 [==============================] - 14s 234us/step - loss: 0.0995 - acc: 0.97
Epoch 18/20
60000/60000 [==============================] - 15s 248us/step - loss: 0.0928 - acc: 0.97
Epoch 19/20
60000/60000 [==============================] - 15s 245us/step - loss: 0.0934 - acc: 0.97
Epoch 20/20
60000/60000 [==============================] - 16s 260us/step - loss: 0.0903 - acc: 0.97
```

```
#Evaluate your model with accuracy and plot of (NUmber of epoches VS train_and_val_loss)
#Train accuracy
score = model_drop.evaluate(X_train, Y_train, verbose=0)
print('Train score:', score[0])
print('Train accuracy:', score[1]*100)
print('\n********************** *********************\n')
#test accuracy
score = model_drop.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1]*100)
fig,ax = plt.subplots(1,1)
```

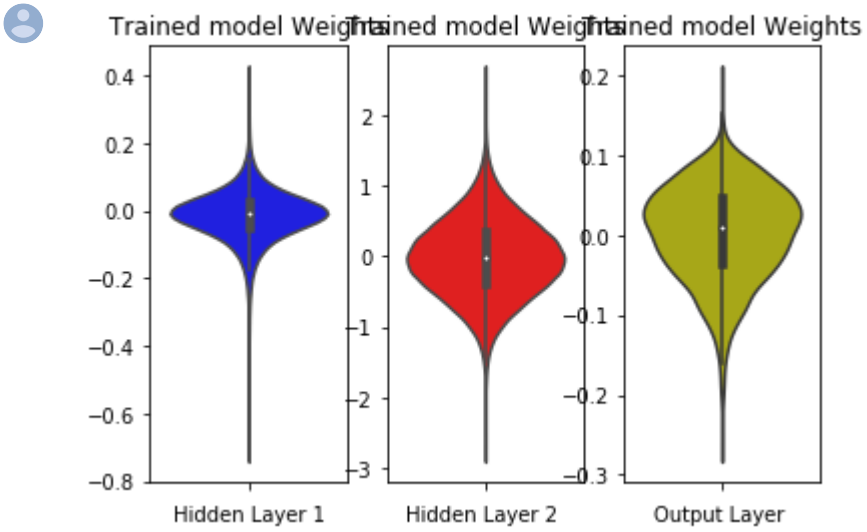
```
ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')
# list of epoch numbers
x = list(range(1,nb_epoch+1))
# print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=
# we will get val_loss and val_acc only when you pass the paramter validation_data
# val_loss : validation loss
# val_acc : validation accuracy
# loss : training loss
# acc : train accuracy
# for each key in histrory.histrory we will have a list of length equal to number of epochs
vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
```

```
Train score: 0.02664580340325483
Train accuracy: 99.25833333333334

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

Test score: 0.08111033427524962
Test accuracy: 97.77
```




```
w_after = model_drop.get_weights()
h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
out_w = w_after[4].flatten().reshape(-1,1)
fig = plt.figure()
plt.title("Weight matrices after model trained")

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

plt.subplot(1, 3, 2)
plt.title("Trained model Weights")
```

```
ax = sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden Layer 2 ')

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



4. MLP + ReLU + adam + dropout+ batch_normalization

```
# https://stackoverflow.com/questions/34716454/where-do-i-call-the-batchnormalization-functio
from keras.layers import Dropout
model_drop = Sequential()
model_drop.add(Dense(610, activation='relu', input_shape=(input_dim,), kernel_initializer=Ran
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))
model_drop.add(Dense(325, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))
model_drop.add(Dense(output_dim, activation='softmax'))
model_drop.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_10 (Dense)             (None, 610)               478850    
_________________________________________________________________
batch_normalization_3 (Batch (None, 610)               2440      
_________________________________________________________________
dropout_3 (Dropout)          (None, 610)               0         
_________________________________________________________________
dense_11 (Dense)             (None, 325)               198575    
_________________________________________________________________
batch_normalization_4 (Batch (None, 325)               1300      
_________________________________________________________________
dropout_4 (Dropout)          (None, 325)               0         
_________________________________________________________________
dense_12 (Dense)             (None, 10)                3260      
=================================================================
Total params: 684,425
Trainable params: 682,555
Non-trainable params: 1,870
_________________________________________________________________
```

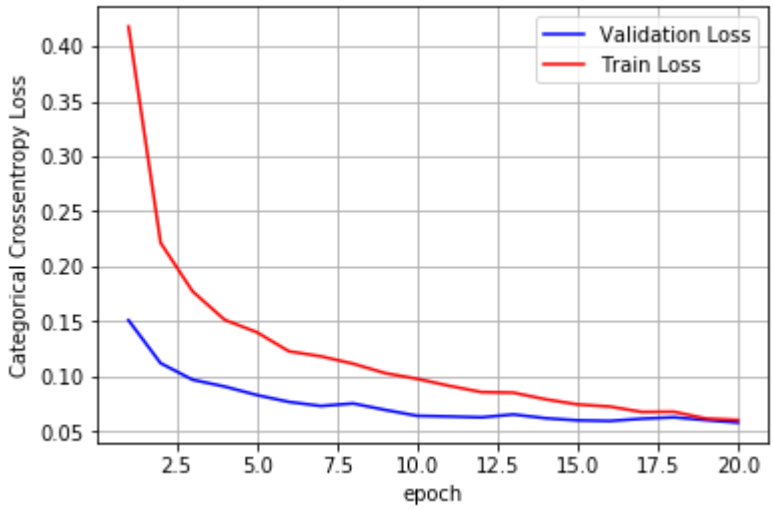
```
model_drop.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=20, verbose=1, valid
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 25s 414us/step - loss: 0.4180 - acc: 0.87
Epoch 2/20
60000/60000 [==============================] - 20s 334us/step - loss: 0.2214 - acc: 0.93
Epoch 3/20
60000/60000 [==============================] - 20s 334us/step - loss: 0.1771 - acc: 0.94
Epoch 4/20
60000/60000 [==============================] - 18s 307us/step - loss: 0.1513 - acc: 0.95
Epoch 5/20
60000/60000 [==============================] - 19s 319us/step - loss: 0.1400 - acc: 0.95
Epoch 6/20
60000/60000 [==============================] - 18s 294us/step - loss: 0.1227 - acc: 0.96
Epoch 7/20
60000/60000 [==============================] - 18s 305us/step - loss: 0.1181 - acc: 0.96
Epoch 8/20
60000/60000 [==============================] - 19s 310us/step - loss: 0.1114 - acc: 0.96
Epoch 9/20
60000/60000 [==============================] - 19s 310us/step - loss: 0.1029 - acc: 0.96
Epoch 10/20
60000/60000 [==============================] - 19s 314us/step - loss: 0.0977 - acc: 0.96
Epoch 11/20
60000/60000 [==============================] - 18s 306us/step - loss: 0.0913 - acc: 0.97
Epoch 12/20
60000/60000 [==============================] - 19s 310us/step - loss: 0.0856 - acc: 0.97
Epoch 13/20
60000/60000 [==============================] - 18s 303us/step - loss: 0.0851 - acc: 0.97
Epoch 14/20
60000/60000 [==============================] - 18s 303us/step - loss: 0.0791 - acc: 0.97
Epoch 15/20
60000/60000 [==============================] - 18s 306us/step - loss: 0.0744 - acc: 0.97
Epoch 16/20
60000/60000 [==============================] - 18s 302us/step - loss: 0.0725 - acc: 0.97
Epoch 17/20
60000/60000 [==============================] - 18s 304us/step - loss: 0.0675 - acc: 0.97
Epoch 18/20
60000/60000 [==============================] - 18s 301us/step - loss: 0.0677 - acc: 0.97
Epoch 19/20
60000/60000 [==============================] - 18s 300us/step - loss: 0.0615 - acc: 0.98
Epoch 20/20
60000/60000 [==============================] - 19s 310us/step - loss: 0.0602 - acc: 0.98
```

```
#Evaluate your model with accuracy and plot of (NUmber of epoches VS train_and_val_loss)
#Train accuracy
score = model_drop.evaluate(X_train, Y_train, verbose=0)
print('Train score:', score[0])
print('Train accuracy:', score[1]*100)
print('\n********************** *********************\n')
#test accuracy
score = model_drop.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1]*100)
fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')
```

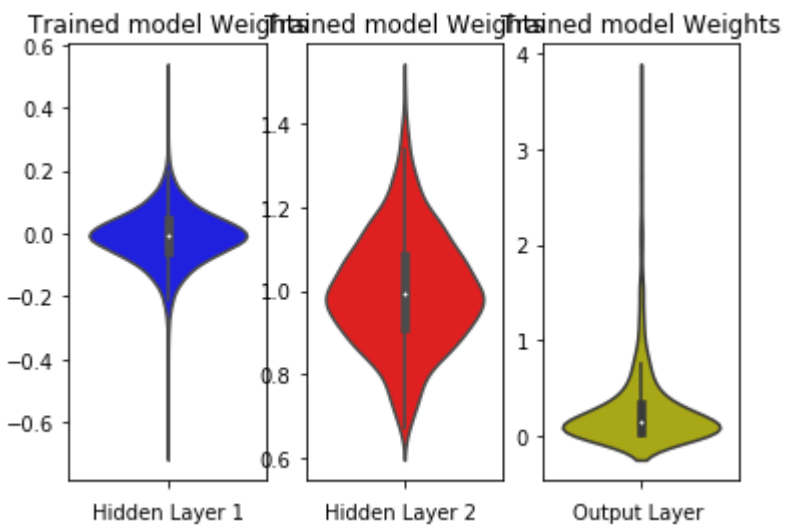
```
# list of epoch numbers
x = list(range(1,nb_epoch+1))
# print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=
# we will get val_loss and val_acc only when you pass the paramter validation_data
# val_loss : validation loss
# val_acc : validation accuracy
# loss : training loss
# acc : train accuracy
# for each key in histrory.histrory we will have a list of length equal to number of epochs
vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
```

```
Train score: 0.014805679358745692
Train accuracy: 99.53666666666666

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

Test score: 0.05782464738052222
Test accuracy: 98.19
```




```
w_after = model_drop.get_weights()
h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
out_w = w_after[4].flatten().reshape(-1,1)
fig = plt.figure()
plt.title("Weight matrices after model trained")

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

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

```
plt.xlabel('Hidden Layer 2 ')

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



Model 2 -- with 3 Hidden layers

1. MLP + ReLU + adam

```
# Multilayer perceptron
# https://arxiv.org/pdf/1707.09725.pdf#page=95
# for relu layers
# If we sample weights from a normal distribution N(0,σ) we satisfy this condition with σ=√(2
# h1 => σ=√(2/(fan_in) = 0.062 => N(0,σ) = N(0,0.062)
# h2 => σ=√(2/(fan_in) = 0.125 => N(0,σ) = N(0,0.125)
# out => σ=√(2/(fan_in+1) = 0.120 => N(0,σ) = N(0,0.120)
model_relu = Sequential()
model_relu.add(Dense(610, activation='relu', input_shape=(input_dim,), kernel_initializer=Ran
model_relu.add(Dense(420, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev
model_relu.add(Dense(210, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev
model_relu.add(Dense(output_dim, activation='softmax'))
model_relu.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_13 (Dense)             (None, 610)               478850    
_________________________________________________________________
dense_14 (Dense)             (None, 420)               256620    
_________________________________________________________________
dense_15 (Dense)             (None, 210)               88410     
_________________________________________________________________
dense_16 (Dense)             (None, 10)                2110      
=================================================================
Total params: 825,990
Trainable params: 825,990
Non-trainable params: 0
_________________________________________________________________
```

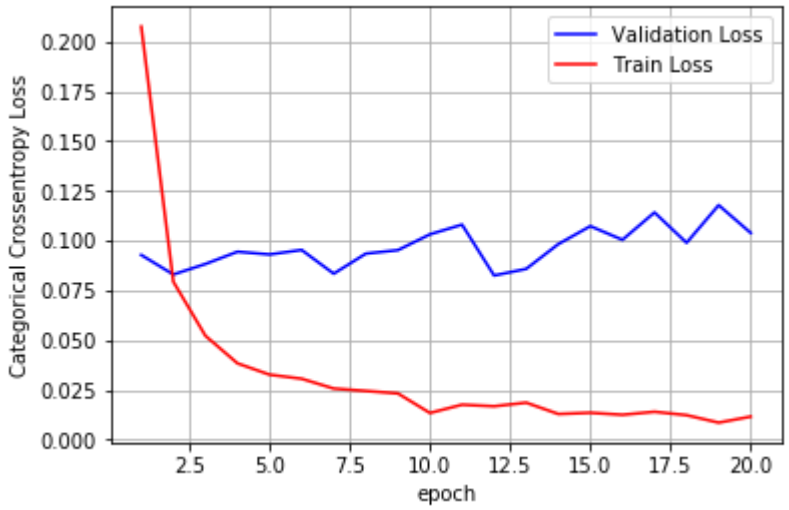
```
model_relu.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
history = model_relu.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1,
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 20s 330us/step - loss: 0.2076 - acc: 0.93
Epoch 2/20
60000/60000 [==============================] - 14s 240us/step - loss: 0.0794 - acc: 0.97
Epoch 3/20
60000/60000 [==============================] - 14s 240us/step - loss: 0.0522 - acc: 0.98
Epoch 4/20
60000/60000 [==============================] - 14s 239us/step - loss: 0.0383 - acc: 0.98
Epoch 5/20
60000/60000 [==============================] - 15s 244us/step - loss: 0.0326 - acc: 0.98
Epoch 6/20
60000/60000 [==============================] - 14s 240us/step - loss: 0.0306 - acc: 0.99
Epoch 7/20
60000/60000 [==============================] - 14s 236us/step - loss: 0.0256 - acc: 0.99
Epoch 8/20
60000/60000 [==============================] - 14s 234us/step - loss: 0.0244 - acc: 0.99
Epoch 9/20
60000/60000 [==============================] - 14s 235us/step - loss: 0.0232 - acc: 0.99
Epoch 10/20
60000/60000 [==============================] - 14s 237us/step - loss: 0.0134 - acc: 0.99
Epoch 11/20
60000/60000 [==============================] - 19s 324us/step - loss: 0.0175 - acc: 0.99
Epoch 12/20
60000/60000 [==============================] - 16s 271us/step - loss: 0.0168 - acc: 0.99
Epoch 13/20
60000/60000 [==============================] - 14s 238us/step - loss: 0.0186 - acc: 0.99
Epoch 14/20
60000/60000 [==============================] - 14s 237us/step - loss: 0.0129 - acc: 0.99
Epoch 15/20
60000/60000 [==============================] - 14s 240us/step - loss: 0.0135 - acc: 0.99
Epoch 16/20
60000/60000 [==============================] - 14s 238us/step - loss: 0.0125 - acc: 0.99
Epoch 17/20
60000/60000 [==============================] - 14s 236us/step - loss: 0.0140 - acc: 0.99
Epoch 18/20
60000/60000 [==============================] - 14s 237us/step - loss: 0.0123 - acc: 0.99
Epoch 19/20
60000/60000 [==============================] - 15s 245us/step - loss: 0.0085 - acc: 0.99
Epoch 20/20
60000/60000 [==============================] - 14s 237us/step - loss: 0.0115 - acc: 0.99
```

```
#Evualate your model with accuracy and plot of (NUmber of epoches VS train_and_val_loss)
#Train accuracy
score = model_relu.evaluate(X_train, Y_train, verbose=0)
print('Train score:', score[0])
print('Train accuracy:', score[1]*100)
print('\n********************** *********************\n')
#test accuracy
score = model_relu.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1]*100)
fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')
```

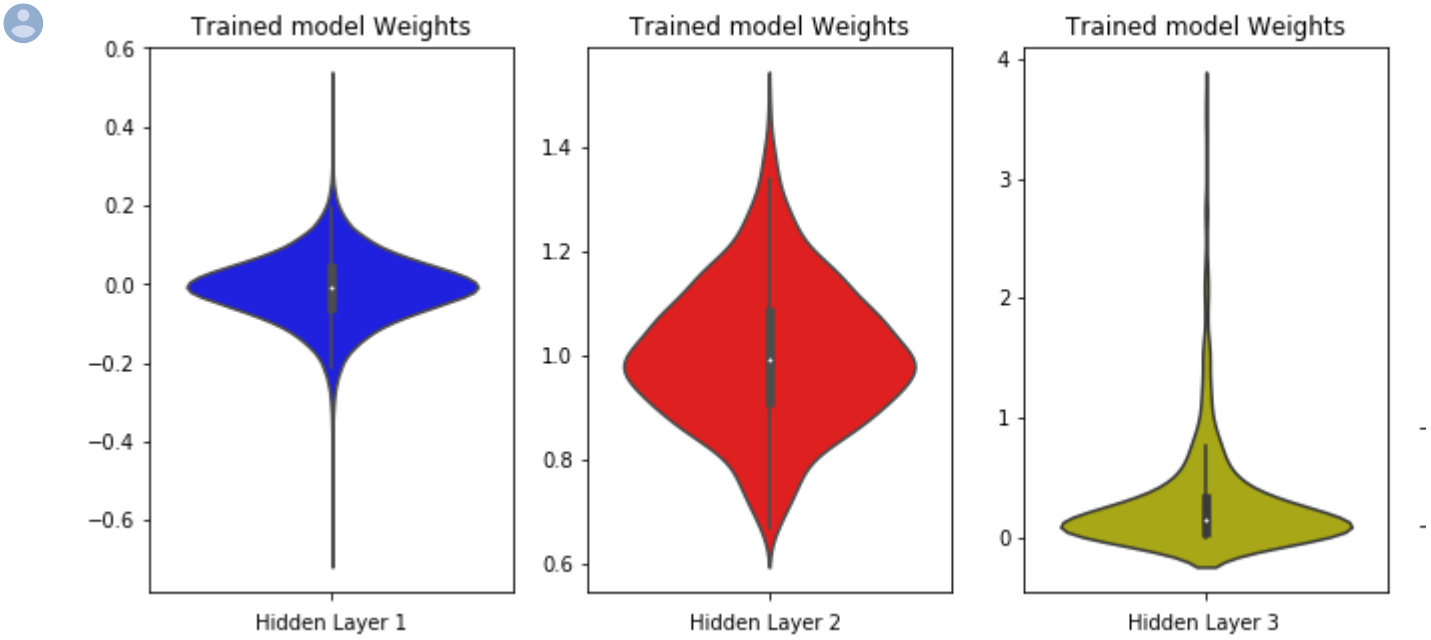
```
# list of epoch numbers
x = list(range(1,nb_epoch+1))
# print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=
# we will get val_loss and val_acc only when you pass the paramter validation_data
# val_loss : validation loss
# val_acc : validation accuracy
# loss : training loss
# acc : train accuracy
# for each key in histrory.histrory we will have a list of length equal to number of epochs
vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
```

```
Train score: 0.011968852381023158
Train accuracy: 99.63833333333334

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

Test score: 0.1038783551045065
Test accuracy: 97.99
```




```
w_after = model_drop.get_weights()
h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
h3_w = w_after[4].flatten().reshape(-1,1)
out_w = w_after[6].flatten().reshape(-1,1)
fig = plt.figure(figsize=(15,5))
plt.title("Weight matrices after model trained")

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

plt.subplot(1, 4, 2)
plt.title("Trained model Weights")
```

```
ax = sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden Layer 2 ')

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

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



2. MLP + ReLU + adam +batch_normalization

```
from keras.layers.normalization import BatchNormalization
model_batch = Sequential()
model_batch.add(Dense(610, activation='relu', input_shape=(input_dim,), kernel_initializer=Ra
model_batch.add(BatchNormalization())
model_batch.add(Dense(420, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stdde
model_batch.add(BatchNormalization())
model_batch.add(Dense(210, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stdde
model_batch.add(BatchNormalization())
model_batch.add(Dense(output_dim, activation='softmax'))
model_batch.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_17 (Dense)             (None, 610)               478850    
_________________________________________________________________
batch_normalization_5 (Batch (None, 610)               2440      
_________________________________________________________________
dense_18 (Dense)             (None, 420)               256620    
_________________________________________________________________
batch_normalization_6 (Batch (None, 420)               1680      
_________________________________________________________________
dense_19 (Dense)             (None, 210)               88410     
_________________________________________________________________
batch_normalization_7 (Batch (None, 210)               840       
_________________________________________________________________
dense_20 (Dense)             (None, 10)                2110      
=================================================================
Total params: 830,950
Trainable params: 828,470
Non-trainable params: 2,480
_________________________________________________________________
```

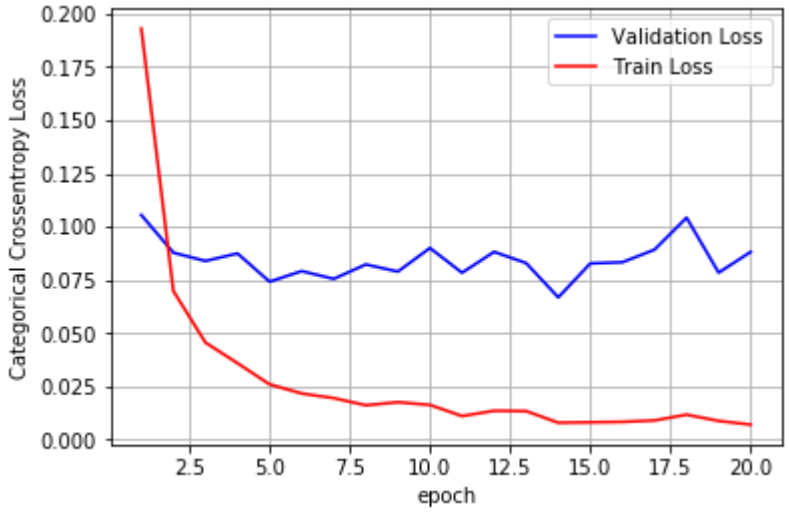
```
model_batch.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
history = model_batch.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 29s 490us/step - loss: 0.1931 - acc: 0.94
Epoch 2/20
60000/60000 [==============================] - 22s 373us/step - loss: 0.0697 - acc: 0.97
Epoch 3/20
60000/60000 [==============================] - 20s 337us/step - loss: 0.0455 - acc: 0.98
Epoch 4/20
60000/60000 [==============================] - 21s 342us/step - loss: 0.0358 - acc: 0.98
Epoch 5/20
60000/60000 [==============================] - 22s 370us/step - loss: 0.0258 - acc: 0.99
Epoch 6/20
60000/60000 [==============================] - 24s 394us/step - loss: 0.0216 - acc: 0.99
Epoch 7/20
60000/60000 [==============================] - 21s 351us/step - loss: 0.0194 - acc: 0.99
Epoch 8/20
60000/60000 [==============================] - 21s 347us/step - loss: 0.0160 - acc: 0.99
Epoch 9/20
60000/60000 [==============================] - 21s 358us/step - loss: 0.0174 - acc: 0.99
Epoch 10/20
60000/60000 [==============================] - 20s 334us/step - loss: 0.0162 - acc: 0.99
Epoch 11/20
60000/60000 [==============================] - 20s 329us/step - loss: 0.0109 - acc: 0.99
Epoch 12/20
60000/60000 [==============================] - 22s 367us/step - loss: 0.0134 - acc: 0.99
Epoch 13/20
60000/60000 [==============================] - 23s 378us/step - loss: 0.0133 - acc: 0.99
Epoch 14/20
60000/60000 [==============================] - 23s 390us/step - loss: 0.0078 - acc: 0.99
Epoch 15/20
60000/60000 [==============================] - 21s 349us/step - loss: 0.0080 - acc: 0.99
Epoch 16/20
60000/60000 [==============================] - 19s 323us/step - loss: 0.0082 - acc: 0.99
Epoch 17/20
60000/60000 [==============================] - 15s 243us/step - loss: 0.0089 - acc: 0.99
Epoch 18/20
60000/60000 [==============================] - 14s 228us/step - loss: 0.0116 - acc: 0.99
Epoch 19/20
60000/60000 [==============================] - 15s 258us/step - loss: 0.0086 - acc: 0.99
Epoch 20/20
60000/60000 [==============================] - 16s 263us/step - loss: 0.0069 - acc: 0.99
```

```
#Evaluate your model with accuracy and plot of (NUmber of epoches VS train_and_val_loss)
#Train accuracy
score = model_batch.evaluate(X_train, Y_train, verbose=0)
print('Train score:', score[0])
print('Train accuracy:', score[1]*100)
print('\n********************** *********************\n')
#test accuracy
score = model_batch.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1]*100)
fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')
```

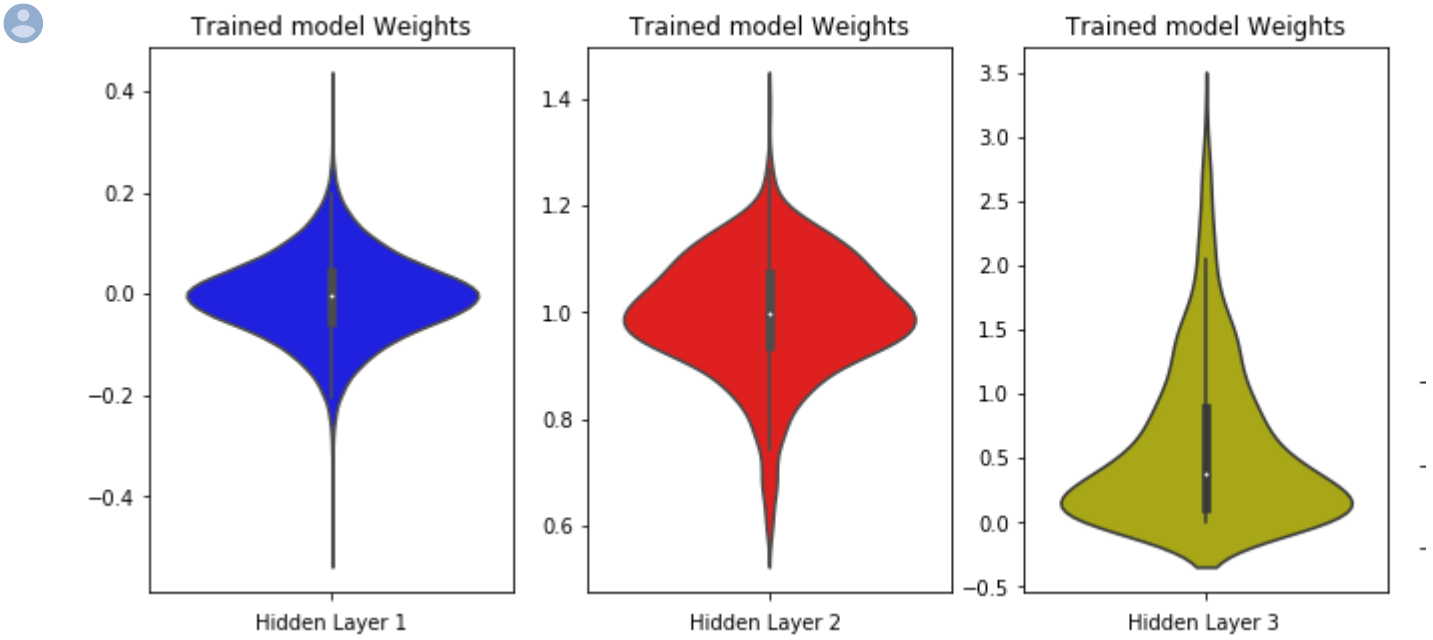
```
# list of epoch numbers
x = list(range(1,nb_epoch+1))
# print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=
# we will get val_loss and val_acc only when you pass the paramter validation_data
# val_loss : validation loss
# val_acc : validation accuracy
# loss : training loss
# acc : train accuracy
# for each key in histrory.histrory we will have a list of length equal to number of epochs
vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
```

```
Train score: 0.00419184478967436
Train accuracy: 99.87833333333333

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

Test score: 0.08813276136659533
Test accuracy: 98.03
```




```
w_after = model_batch.get_weights()
h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
h3_w = w_after[4].flatten().reshape(-1,1)
out_w = w_after[6].flatten().reshape(-1,1)
fig = plt.figure(figsize=(15,5))
plt.title("Weight matrices after model trained")

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

plt.subplot(1, 4, 2)
```

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

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

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



3. MLP + ReLU + adam +dropout

```
# https://stackoverflow.com/questions/34716454/where-do-i-call-the-batchnormalization-functio
from keras.layers import Dropout
model_drop = Sequential()
model_drop.add(Dense(610, activation='relu', input_shape=(input_dim,), kernel_initializer=Ran
#model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))
model_drop.add(Dense(420, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev
#model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))
model_drop.add(Dense(210, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev
#model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))
model_drop.add(Dense(output_dim, activation='softmax'))
model_drop.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_21 (Dense)             (None, 610)               478850    
_________________________________________________________________
dropout_5 (Dropout)          (None, 610)               0         
_________________________________________________________________
dense_22 (Dense)             (None, 420)               256620    
_________________________________________________________________
dropout_6 (Dropout)          (None, 420)               0         
_________________________________________________________________
dense_23 (Dense)             (None, 210)               88410     
_________________________________________________________________
dropout_7 (Dropout)          (None, 210)               0         
_________________________________________________________________
dense_24 (Dense)             (None, 10)                2110      
=================================================================
Total params: 825,990
Trainable params: 825,990
Non-trainable params: 0
_________________________________________________________________
```

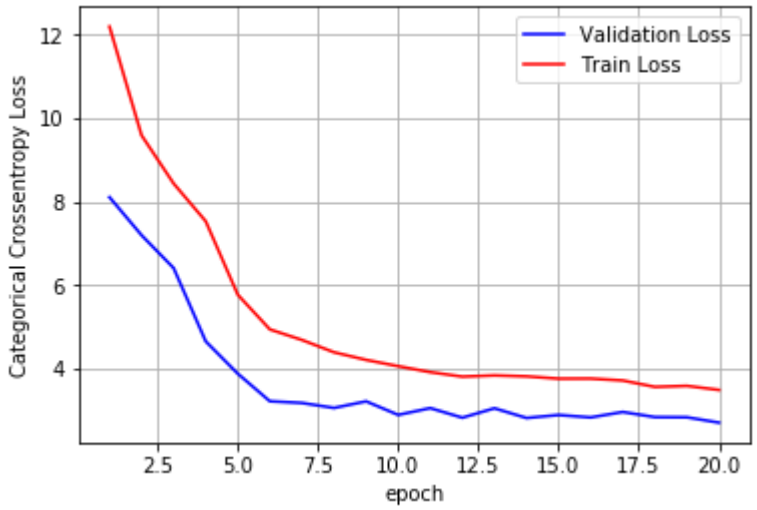
```
model_drop.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1,
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 13s 222us/step - loss: 12.1946 - acc: 0.2
Epoch 2/20
60000/60000 [==============================] - 12s 197us/step - loss: 9.5885 - acc: 0.39
Epoch 3/20
60000/60000 [==============================] - 12s 200us/step - loss: 8.4335 - acc: 0.47
Epoch 4/20
60000/60000 [==============================] - 12s 196us/step - loss: 7.5302 - acc: 0.52
Epoch 5/20
60000/60000 [==============================] - 11s 185us/step - loss: 5.7684 - acc: 0.63
Epoch 6/20
60000/60000 [==============================] - 10s 175us/step - loss: 4.9382 - acc: 0.68
Epoch 7/20
60000/60000 [==============================] - 10s 174us/step - loss: 4.6853 - acc: 0.70
Epoch 8/20
60000/60000 [==============================] - 10s 174us/step - loss: 4.3897 - acc: 0.72
Epoch 9/20
60000/60000 [==============================] - 10s 174us/step - loss: 4.2075 - acc: 0.73
Epoch 10/20
60000/60000 [==============================] - 10s 175us/step - loss: 4.0565 - acc: 0.74
Epoch 11/20
60000/60000 [==============================] - 11s 184us/step - loss: 3.9138 - acc: 0.75
Epoch 12/20
60000/60000 [==============================] - 10s 174us/step - loss: 3.8066 - acc: 0.76
Epoch 13/20
60000/60000 [==============================] - 10s 174us/step - loss: 3.8358 - acc: 0.75
Epoch 14/20
60000/60000 [==============================] - 10s 174us/step - loss: 3.8129 - acc: 0.76
Epoch 15/20
60000/60000 [==============================] - 10s 174us/step - loss: 3.7580 - acc: 0.76
Epoch 16/20
60000/60000 [==============================] - 10s 174us/step - loss: 3.7595 - acc: 0.76
Epoch 17/20
60000/60000 [==============================] - 10s 174us/step - loss: 3.7141 - acc: 0.76
Epoch 18/20
60000/60000 [==============================] - 11s 177us/step - loss: 3.5606 - acc: 0.77
Epoch 19/20
60000/60000 [==============================] - 10s 174us/step - loss: 3.5846 - acc: 0.77
Epoch 20/20
60000/60000 [==============================] - 10s 173us/step - loss: 3.4881 - acc: 0.78
```

```
#Evaluate your model with accuracy and plot of (NUmber of epoches VS train_and_val_loss)
#Train accuracy
score = model_drop.evaluate(X_train, Y_train, verbose=0)
print('Train score:', score[0])
print('Train accuracy:', score[1]*100)
print('\n********************** *********************\n')
#test accuracy
score = model_drop.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1]*100)
fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')
```

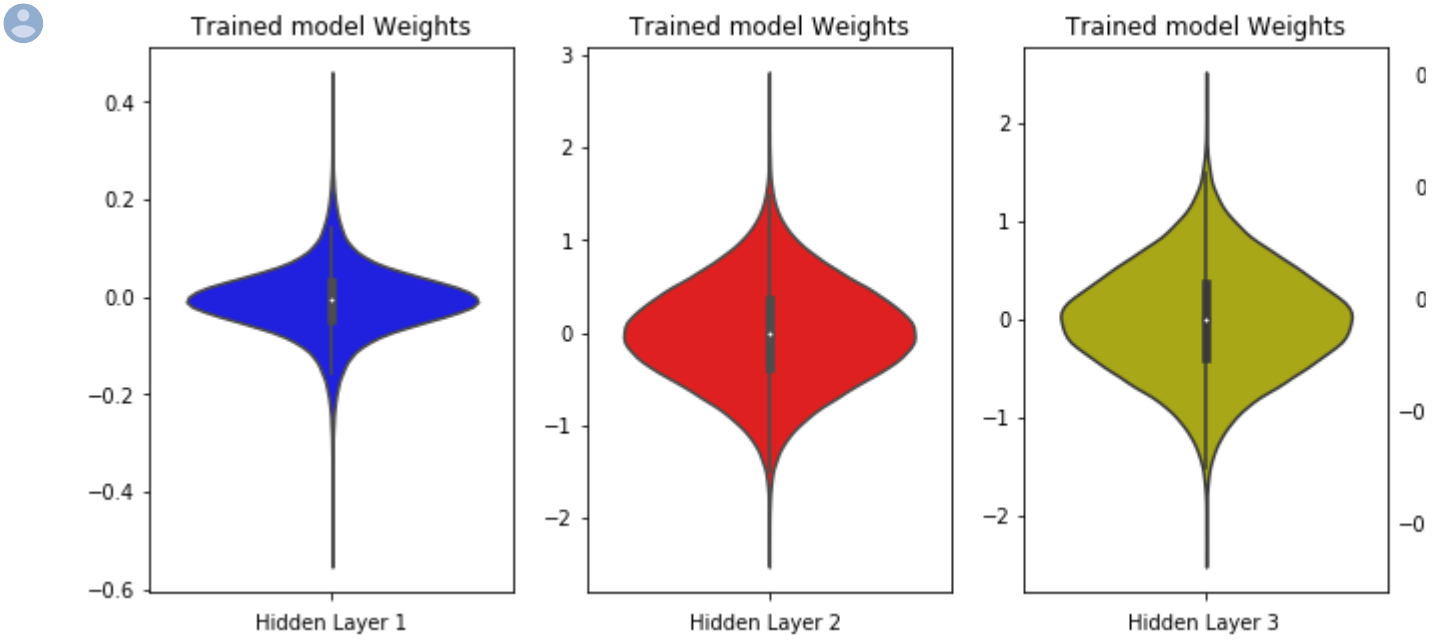
```
# list of epoch numbers
x = list(range(1,nb_epoch+1))
# print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=
# we will get val_loss and val_acc only when you pass the paramter validation_data
# val_loss : validation loss
# val_acc : validation accuracy
# loss : training loss
# acc : train accuracy
# for each key in histrory.histrory we will have a list of length equal to number of epochs
vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
```

```
Train score: 2.7385955852190653
Train accuracy: 82.94666666666667

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

Test score: 2.7042304149627685
Test accuracy: 83.14
```




```
w_after = model_drop.get_weights()
h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
h3_w = w_after[4].flatten().reshape(-1,1)
out_w = w_after[6].flatten().reshape(-1,1)
fig = plt.figure(figsize=(15,5))
plt.title("Weight matrices after model trained")
plt.subplot(1, 4, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

plt.subplot(1, 4, 2)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h2_w, color='r')
```

```
plt.xlabel('Hidden Layer 2 ')

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

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



4. MLP + ReLU + adam +dropout+batch_normalization

```
# https://stackoverflow.com/questions/34716454/where-do-i-call-the-batchnormalization-functio
from keras.layers import Dropout
model_drop = Sequential()
model_drop.add(Dense(610, activation='relu', input_shape=(input_dim,), kernel_initializer=Ran
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))
model_drop.add(Dense(420, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))
model_drop.add(Dense(210, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))
model_drop.add(Dense(output_dim, activation='softmax'))
model_drop.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_25 (Dense)             (None, 610)               478850    
_________________________________________________________________
batch_normalization_8 (Batch (None, 610)               2440      
_________________________________________________________________
dropout_8 (Dropout)          (None, 610)               0         
_________________________________________________________________
dense_26 (Dense)             (None, 420)               256620    
_________________________________________________________________
batch_normalization_9 (Batch (None, 420)               1680      
_________________________________________________________________
dropout_9 (Dropout)          (None, 420)               0         
_________________________________________________________________
dense_27 (Dense)             (None, 210)               88410     
_________________________________________________________________
batch_normalization_10 (Batc (None, 210)               840       
_________________________________________________________________
dropout_10 (Dropout)         (None, 210)               0         
_________________________________________________________________
dense_28 (Dense)             (None, 10)                2110      
=================================================================
Total params: 830,950
Trainable params: 828,470
Non-trainable params: 2,480
_________________________________________________________________
```

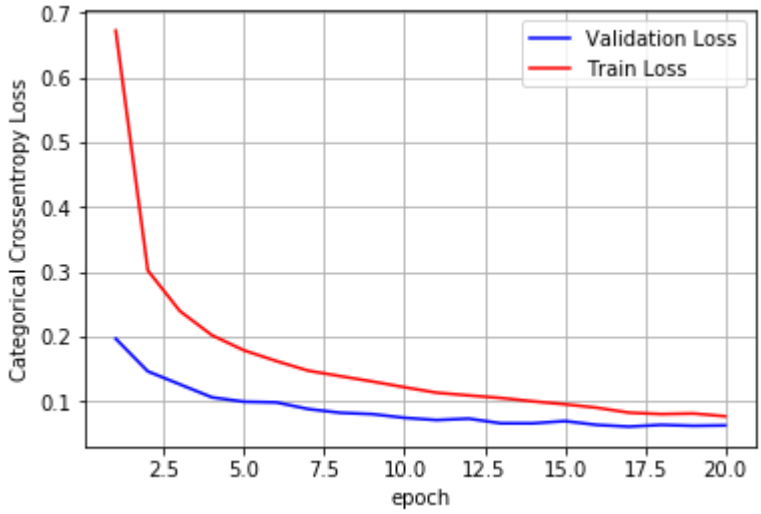
```
model_drop.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1,
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 17s 279us/step - loss: 0.6729 - acc: 0.79
Epoch 2/20
60000/60000 [==============================] - 14s 236us/step - loss: 0.3022 - acc: 0.90
Epoch 3/20
60000/60000 [==============================] - 13s 219us/step - loss: 0.2394 - acc: 0.92
Epoch 4/20
60000/60000 [==============================] - 13s 225us/step - loss: 0.2020 - acc: 0.93
Epoch 5/20
60000/60000 [==============================] - 13s 212us/step - loss: 0.1787 - acc: 0.94
Epoch 6/20
60000/60000 [==============================] - 14s 234us/step - loss: 0.1623 - acc: 0.95
Epoch 7/20
60000/60000 [==============================] - 14s 226us/step - loss: 0.1473 - acc: 0.95
Epoch 8/20
60000/60000 [==============================] - 15s 251us/step - loss: 0.1389 - acc: 0.95
Epoch 9/20
60000/60000 [==============================] - 19s 312us/step - loss: 0.1306 - acc: 0.96
Epoch 10/20
60000/60000 [==============================] - 17s 288us/step - loss: 0.1218 - acc: 0.96
Epoch 11/20
60000/60000 [==============================] - 19s 320us/step - loss: 0.1133 - acc: 0.96
Epoch 12/20
60000/60000 [==============================] - 19s 314us/step - loss: 0.1091 - acc: 0.96
Epoch 13/20
60000/60000 [==============================] - 18s 295us/step - loss: 0.1052 - acc: 0.96
Epoch 14/20
60000/60000 [==============================] - 17s 282us/step - loss: 0.1000 - acc: 0.96
Epoch 15/20
60000/60000 [==============================] - 16s 266us/step - loss: 0.0954 - acc: 0.97
Epoch 16/20
60000/60000 [==============================] - 16s 272us/step - loss: 0.0901 - acc: 0.97
Epoch 17/20
60000/60000 [==============================] - 17s 280us/step - loss: 0.0825 - acc: 0.97
Epoch 18/20
60000/60000 [==============================] - 19s 310us/step - loss: 0.0802 - acc: 0.97
Epoch 19/20
60000/60000 [==============================] - 20s 336us/step - loss: 0.0811 - acc: 0.97
Epoch 20/20
60000/60000 [==============================] - 17s 283us/step - loss: 0.0769 - acc: 0.97
```

```
#Evaluate your model with accuracy and plot of (NUmber of epoches VS train_and_val_loss)
#Train accuracy
score = model_drop.evaluate(X_train, Y_train, verbose=0)
print('Train score:', score[0])
print('Train accuracy:', score[1]*100)
print('\n********************** *********************\n')
#test accuracy
score = model_drop.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1]*100)
fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')
```

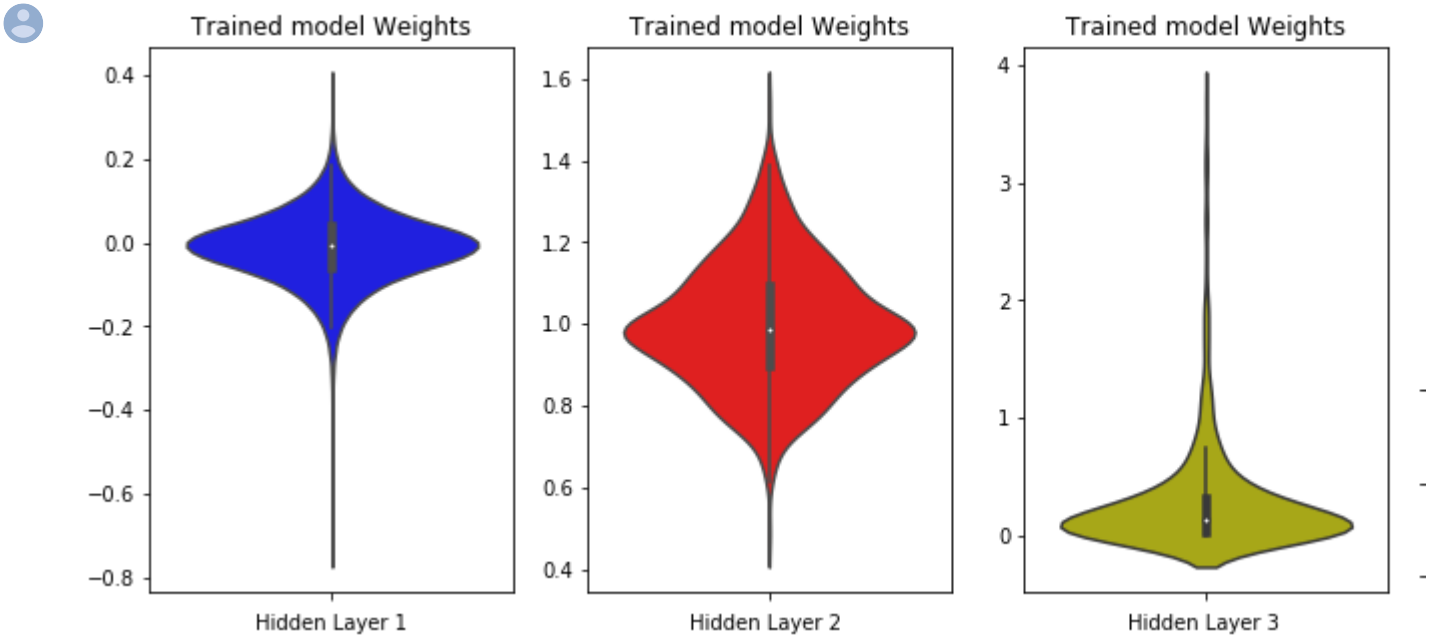
```
# list of epoch numbers
x = list(range(1,nb_epoch+1))
# print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=
# we will get val_loss and val_acc only when you pass the paramter validation_data
# val_loss : validation loss
# val_acc : validation accuracy
# loss : training loss
# acc : train accuracy
# for each key in histrory.histrory we will have a list of length equal to number of epochs
vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
```

```
Train score: 0.02124301015394934
Train accuracy: 99.33166666666666

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

Test score: 0.0627561581715534
Test accuracy: 98.21
```




```
w_after = model_drop.get_weights()
h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
h3_w = w_after[4].flatten().reshape(-1,1)
out_w = w_after[6].flatten().reshape(-1,1)
fig = plt.figure(figsize=(15,5))
plt.title("Weight matrices after model trained")
plt.subplot(1, 4, 1)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

plt.subplot(1, 4, 2)
plt.title("Trained model Weights")
ax = sns.violinplot(y=h2_w, color='r')
```

```
plt.xlabel('Hidden Layer 2 ')

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

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



Model 3 -- with 5 Hidden layers

1. MLP + ReLU + adam

```
# Multilayer perceptron
# https://arxiv.org/pdf/1707.09725.pdf#page=95
# for relu layers
# If we sample weights from a normal distribution N(0,σ) we satisfy this condition with σ=√(2
# h1 => σ=√(2/(fan_in) = 0.062 => N(0,σ) = N(0,0.062)
# h2 => σ=√(2/(fan_in) = 0.125 => N(0,σ) = N(0,0.125)
# out => σ=√(2/(fan_in+1) = 0.120 => N(0,σ) = N(0,0.120)
model_relu = Sequential()
model_relu.add(Dense(690, activation='relu', input_shape=(input_dim,), kernel_initializer=Ran
model_relu.add(Dense(530, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev
model_relu.add(Dense(412, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev
```

```
model_relu.add(Dense(231, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev
model_relu.add(Dense(112, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev
model_relu.add(Dense(output_dim, activation='softmax'))
model_relu.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_29 (Dense)             (None, 690)               541650    
_________________________________________________________________
dense_30 (Dense)             (None, 530)               366230    
_________________________________________________________________
dense_31 (Dense)             (None, 412)               218772    
_________________________________________________________________
dense_32 (Dense)             (None, 231)               95403     
_________________________________________________________________
dense_33 (Dense)             (None, 112)               25984     
_________________________________________________________________
dense_34 (Dense)             (None, 10)                1130      
=================================================================
Total params: 1,249,169
Trainable params: 1,249,169
Non-trainable params: 0
_________________________________________________________________
```

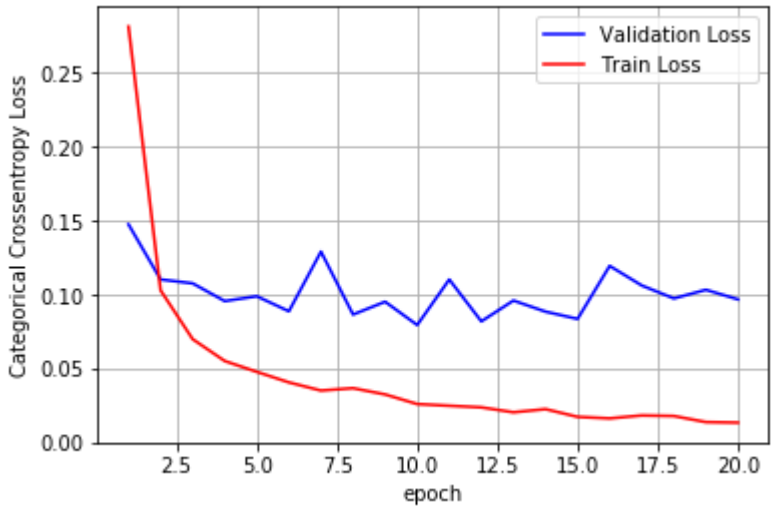
```
model_relu.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
history = model_relu.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1,
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 17s 290us/step - loss: 0.2813 - acc: 0.92
Epoch 2/20
60000/60000 [==============================] - 15s 249us/step - loss: 0.1031 - acc: 0.96
Epoch 3/20
60000/60000 [==============================] - 17s 281us/step - loss: 0.0702 - acc: 0.97
Epoch 4/20
60000/60000 [==============================] - 17s 283us/step - loss: 0.0554 - acc: 0.98
Epoch 5/20
60000/60000 [==============================] - 16s 259us/step - loss: 0.0481 - acc: 0.98
Epoch 6/20
60000/60000 [==============================] - 17s 277us/step - loss: 0.0409 - acc: 0.98
Epoch 7/20
60000/60000 [==============================] - 15s 258us/step - loss: 0.0354 - acc: 0.98
Epoch 8/20
60000/60000 [==============================] - 15s 256us/step - loss: 0.0370 - acc: 0.98
Epoch 9/20
60000/60000 [==============================] - 17s 289us/step - loss: 0.0328 - acc: 0.98
Epoch 10/20
60000/60000 [==============================] - 16s 265us/step - loss: 0.0263 - acc: 0.99
Epoch 11/20
60000/60000 [==============================] - 17s 289us/step - loss: 0.0252 - acc: 0.99
Epoch 12/20
60000/60000 [==============================] - 16s 267us/step - loss: 0.0241 - acc: 0.99
Epoch 13/20
60000/60000 [==============================] - 18s 295us/step - loss: 0.0207 - acc: 0.99
Epoch 14/20
60000/60000 [==============================] - 18s 306us/step - loss: 0.0229 - acc: 0.99
Epoch 15/20
60000/60000 [==============================] - 19s 322us/step - loss: 0.0177 - acc: 0.99
Epoch 16/20
60000/60000 [==============================] - 17s 275us/step - loss: 0.0166 - acc: 0.99
Epoch 17/20
60000/60000 [==============================] - 17s 278us/step - loss: 0.0186 - acc: 0.99
Epoch 18/20
60000/60000 [==============================] - 18s 295us/step - loss: 0.0182 - acc: 0.99
Epoch 19/20
60000/60000 [==============================] - 19s 317us/step - loss: 0.0141 - acc: 0.99
Epoch 20/20
60000/60000 [==============================] - 18s 296us/step - loss: 0.0138 - acc: 0.99
```

```
#Evaluate your model with accuracy and plot of (NUmber of epoches VS train_and_val_loss)
#Train accuracy
score = model_relu.evaluate(X_train, Y_train, verbose=0)
print('Train score:', score[0])
print('Train accuracy:', score[1]*100)
print('\n********************** *********************\n')
#test accuracy
score = model_relu.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1]*100)
fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')
```

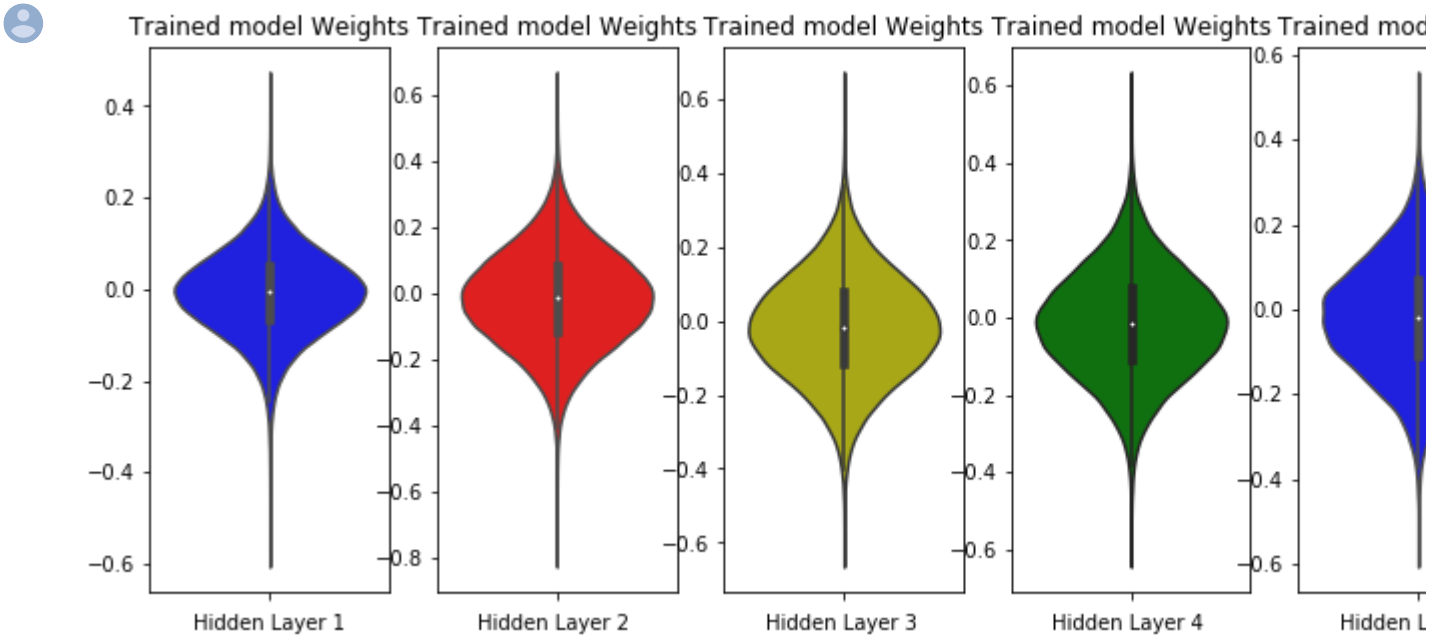
```
# list of epoch numbers
x = list(range(1,nb_epoch+1))
# print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=
# we will get val_loss and val_acc only when you pass the paramter validation_data
# val_loss : validation loss
# val_acc : validation accuracy
# loss : training loss
# acc : train accuracy
# for each key in histrory.histrory we will have a list of length equal to number of epochs
vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
```

```
Train score: 0.007615429904182383
Train accuracy: 99.78333333333333

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

Test score: 0.09702783975718078
Test accuracy: 98.02
```




```
w_after = model_relu.get_weights()
h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
h3_w = w_after[4].flatten().reshape(-1,1)
h4_w = w_after[6].flatten().reshape(-1,1)
h5_w = w_after[8].flatten().reshape(-1,1)
out_w = w_after[10].flatten().reshape(-1,1)
fig = plt.figure(figsize=(15,5))
plt.title("Weight matrices after model trained")

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

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

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

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

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

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



2. MLP + ReLU + adam +batch_normalization

```
# Multilayer perceptron
# https://arxiv.org/pdf/1707.09725.pdf#page=95
```

```
# for relu layers
# If we sample weights from a normal distribution N(0,σ) we satisfy this condition with σ=√(2
# h1 => σ=√(2/(fan_in) = 0.062 => N(0,σ) = N(0,0.062)
# h2 => σ=√(2/(fan_in) = 0.125 => N(0,σ) = N(0,0.125)
# out => σ=√(2/(fan_in+1) = 0.120 => N(0,σ) = N(0,0.120)
model_relu = Sequential()
model_relu.add(Dense(690, activation='relu', input_shape=(input_dim,), kernel_initializer=Ran
model_relu.add(BatchNormalization())
model_relu.add(Dense(530, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev
model_relu.add(BatchNormalization())
model_relu.add(Dense(412, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev
model_relu.add(BatchNormalization())
model_relu.add(Dense(231, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev
model_relu.add(BatchNormalization())
model_relu.add(Dense(112, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev
model_relu.add(BatchNormalization())
model_relu.add(Dense(output_dim, activation='softmax'))
model_relu.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_35 (Dense)             (None, 690)               541650
_________________________________________________________________
batch_normalization_11 (Batc (None, 690)               2760
_________________________________________________________________
dense_36 (Dense)             (None, 530)               366230
_________________________________________________________________
batch_normalization_12 (Batc (None, 530)               2120
_________________________________________________________________
dense_37 (Dense)             (None, 412)               218772
_________________________________________________________________
batch_normalization_13 (Batc (None, 412)               1648
_________________________________________________________________
dense_38 (Dense)             (None, 231)               95403
_________________________________________________________________
batch_normalization_14 (Batc (None, 231)               924
_________________________________________________________________
dense_39 (Dense)             (None, 112)               25984
_________________________________________________________________
batch_normalization_15 (Batc (None, 112)               448
_________________________________________________________________
dense_40 (Dense)             (None, 10)                1130
=================================================================
Total params: 1,257,069
Trainable params: 1,253,119
Non-trainable params: 3,950
_________________________________________________________________
```

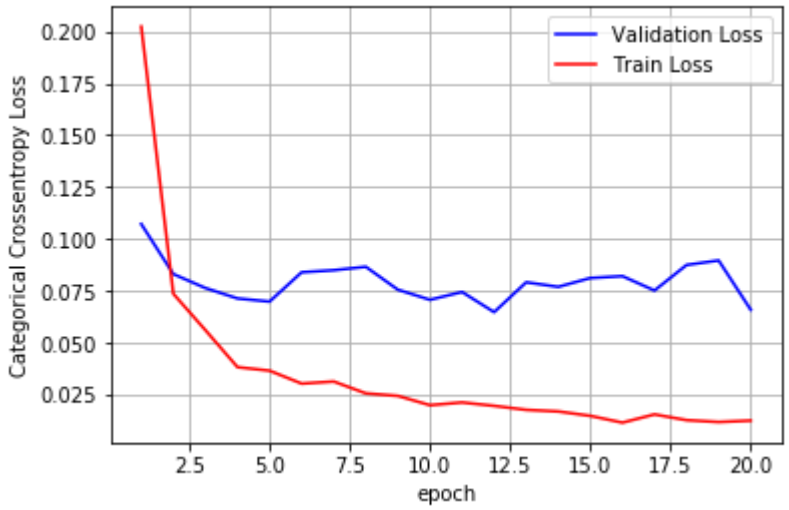
```
model_relu.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
history = model_relu.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1,
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 23s 383us/step - loss: 0.2023 - acc: 0.93
Epoch 2/20
60000/60000 [==============================] - 18s 305us/step - loss: 0.0737 - acc: 0.97
Epoch 3/20
60000/60000 [==============================] - 20s 327us/step - loss: 0.0562 - acc: 0.98
Epoch 4/20
60000/60000 [==============================] - 21s 344us/step - loss: 0.0384 - acc: 0.98
Epoch 5/20
60000/60000 [==============================] - 20s 333us/step - loss: 0.0367 - acc: 0.98
Epoch 6/20
60000/60000 [==============================] - 18s 297us/step - loss: 0.0305 - acc: 0.99
Epoch 7/20
60000/60000 [==============================] - 19s 313us/step - loss: 0.0315 - acc: 0.98
Epoch 8/20
60000/60000 [==============================] - 19s 318us/step - loss: 0.0258 - acc: 0.99
Epoch 9/20
60000/60000 [==============================] - 19s 321us/step - loss: 0.0246 - acc: 0.99
Epoch 10/20
60000/60000 [==============================] - 20s 327us/step - loss: 0.0201 - acc: 0.99
Epoch 11/20
60000/60000 [==============================] - 20s 337us/step - loss: 0.0214 - acc: 0.99
Epoch 12/20
60000/60000 [==============================] - 21s 350us/step - loss: 0.0198 - acc: 0.99
Epoch 13/20
60000/60000 [==============================] - 22s 367us/step - loss: 0.0179 - acc: 0.99
Epoch 14/20
60000/60000 [==============================] - 21s 347us/step - loss: 0.0171 - acc: 0.99
Epoch 15/20
60000/60000 [==============================] - 19s 323us/step - loss: 0.0150 - acc: 0.99
Epoch 16/20
60000/60000 [==============================] - 16s 268us/step - loss: 0.0117 - acc: 0.99
Epoch 17/20
60000/60000 [==============================] - 16s 267us/step - loss: 0.0157 - acc: 0.99
Epoch 18/20
60000/60000 [==============================] - 16s 265us/step - loss: 0.0129 - acc: 0.99
Epoch 19/20
60000/60000 [==============================] - 16s 263us/step - loss: 0.0120 - acc: 0.99
Epoch 20/20
60000/60000 [==============================] - 16s 263us/step - loss: 0.0127 - acc: 0.99
```

```
#Evaluate your model with accuracy and plot of (NUmber of epoches VS train_and_val_loss)
#Train accuracy
score = model_relu.evaluate(X_train, Y_train, verbose=0)
print('Train score:', score[0])
print('Train accuracy:', score[1]*100)
print('\n********************** *********************\n')
#test accuracy
score = model_relu.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1]*100)
fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')
```

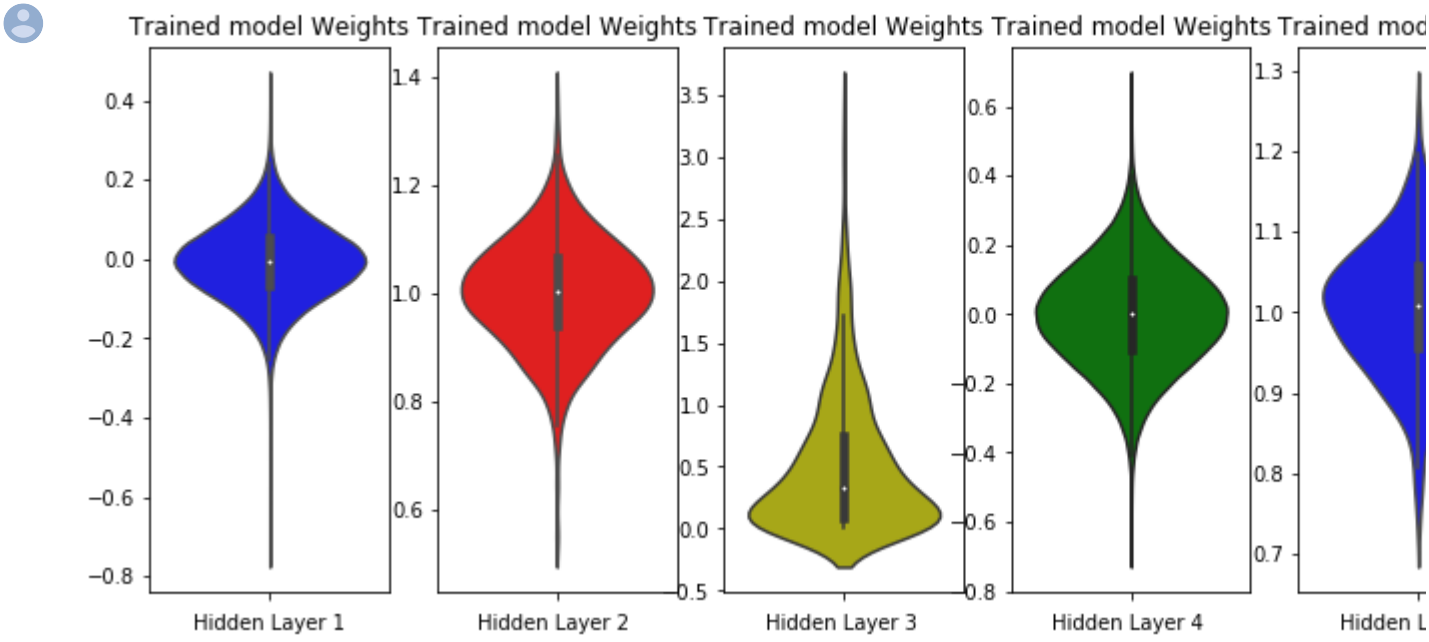
```
# list of epoch numbers
x = list(range(1,nb_epoch+1))
# print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=
# we will get val_loss and val_acc only when you pass the paramter validation_data
# val_loss : validation loss
# val_acc : validation accuracy
# loss : training loss
# acc : train accuracy
# for each key in histrory.histrory we will have a list of length equal to number of epochs
vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
```

```
Train score: 0.006093753856421487
Train accuracy: 99.79833333333333

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

Test score: 0.06601150656397804
Test accuracy: 98.34
```




```
w_after = model_relu.get_weights()
h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
h3_w = w_after[4].flatten().reshape(-1,1)
h4_w = w_after[6].flatten().reshape(-1,1)
h5_w = w_after[8].flatten().reshape(-1,1)
out_w = w_after[10].flatten().reshape(-1,1)
fig = plt.figure(figsize=(15,5))
plt.title("Weight matrices after model trained")

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

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

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

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

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

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



3. MLP + ReLU + adam + dropout

```
# Multilayer perceptron
# https://arxiv.org/pdf/1707.09725.pdf#page=95
```

```
# for relu layers
# If we sample weights from a normal distribution N(0,σ) we satisfy this condition with σ=√(2
# h1 => σ=√(2/(fan_in) = 0.062 => N(0,σ) = N(0,0.062)
# h2 => σ=√(2/(fan_in) = 0.125 => N(0,σ) = N(0,0.125)
# out => σ=√(2/(fan_in+1) = 0.120 => N(0,σ) = N(0,0.120)
model_relu = Sequential()
model_relu.add(Dense(690, activation='relu', input_shape=(input_dim,), kernel_initializer=Ran
#model_relu.add(BatchNormalization())
model_relu.add(Dropout(0.5))
model_relu.add(Dense(530, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev
#model_relu.add(BatchNormalization())
model_relu.add(Dropout(0.5))
model_relu.add(Dense(412, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev
#model_relu.add(BatchNormalization())
model_relu.add(Dropout(0.5))
model_relu.add(Dense(231, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev
#model_relu.add(BatchNormalization())
model_relu.add(Dropout(0.5))
model_relu.add(Dense(112, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev
#model_relu.add(BatchNormalization())
model_relu.add(Dropout(0.5))
model_relu.add(Dense(output_dim, activation='softmax'))
model_relu.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_41 (Dense)             (None, 690)               541650
_________________________________________________________________
dropout_11 (Dropout)         (None, 690)               0
_________________________________________________________________
dense_42 (Dense)             (None, 530)               366230
_________________________________________________________________
dropout_12 (Dropout)         (None, 530)               0
_________________________________________________________________
dense_43 (Dense)             (None, 412)               218772
_________________________________________________________________
dropout_13 (Dropout)         (None, 412)               0
_________________________________________________________________
dense_44 (Dense)             (None, 231)               95403
_________________________________________________________________
dropout_14 (Dropout)         (None, 231)               0
_________________________________________________________________
dense_45 (Dense)             (None, 112)               25984
_________________________________________________________________
dropout_15 (Dropout)         (None, 112)               0
_________________________________________________________________
dense_46 (Dense)             (None, 10)                1130
=================================================================
Total params: 1,249,169
Trainable params: 1,249,169
Non-trainable params: 0
_________________________________________________________________
```

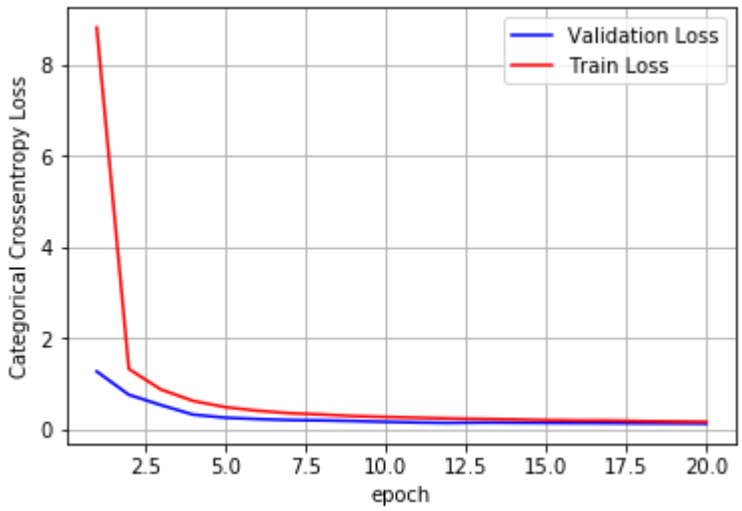
```
model_relu.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
history = model_relu.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1,
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 17s 282us/step - loss: 8.8255 - acc: 0.26
Epoch 2/20
60000/60000 [==============================] - 14s 240us/step - loss: 1.3211 - acc: 0.55
Epoch 3/20
60000/60000 [==============================] - 14s 241us/step - loss: 0.8694 - acc: 0.71
Epoch 4/20
60000/60000 [==============================] - 14s 240us/step - loss: 0.6193 - acc: 0.81
Epoch 5/20
60000/60000 [==============================] - 15s 243us/step - loss: 0.4821 - acc: 0.86
Epoch 6/20
60000/60000 [==============================] - 14s 241us/step - loss: 0.4034 - acc: 0.89
Epoch 7/20
60000/60000 [==============================] - 14s 240us/step - loss: 0.3484 - acc: 0.91
Epoch 8/20
60000/60000 [==============================] - 14s 240us/step - loss: 0.3198 - acc: 0.91
Epoch 9/20
60000/60000 [==============================] - 15s 243us/step - loss: 0.2856 - acc: 0.92
Epoch 10/20
60000/60000 [==============================] - 14s 241us/step - loss: 0.2654 - acc: 0.93
Epoch 11/20
60000/60000 [==============================] - 14s 240us/step - loss: 0.2493 - acc: 0.93
Epoch 12/20
60000/60000 [==============================] - 14s 241us/step - loss: 0.2319 - acc: 0.94
Epoch 13/20
60000/60000 [==============================] - 14s 241us/step - loss: 0.2219 - acc: 0.94
Epoch 14/20
60000/60000 [==============================] - 14s 242us/step - loss: 0.2114 - acc: 0.94
Epoch 15/20
60000/60000 [==============================] - 14s 241us/step - loss: 0.1960 - acc: 0.95
Epoch 16/20
60000/60000 [==============================] - 14s 241us/step - loss: 0.1886 - acc: 0.95
Epoch 17/20
60000/60000 [==============================] - 14s 241us/step - loss: 0.1867 - acc: 0.95
Epoch 18/20
60000/60000 [==============================] - 14s 241us/step - loss: 0.1729 - acc: 0.95
Epoch 19/20
60000/60000 [==============================] - 14s 240us/step - loss: 0.1658 - acc: 0.96
Epoch 20/20
60000/60000 [==============================] - 15s 244us/step - loss: 0.1590 - acc: 0.96
```

```
#Evualate your model with accuracy and plot of (NUmber of epoches VS train_and_val_loss)
#Train accuracy
score = model_relu.evaluate(X_train, Y_train, verbose=0)
print('Train score:', score[0])
print('Train accuracy:', score[1]*100)
print('\n********************** *********************\n')
#test accuracy
score = model_relu.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1]*100)
```

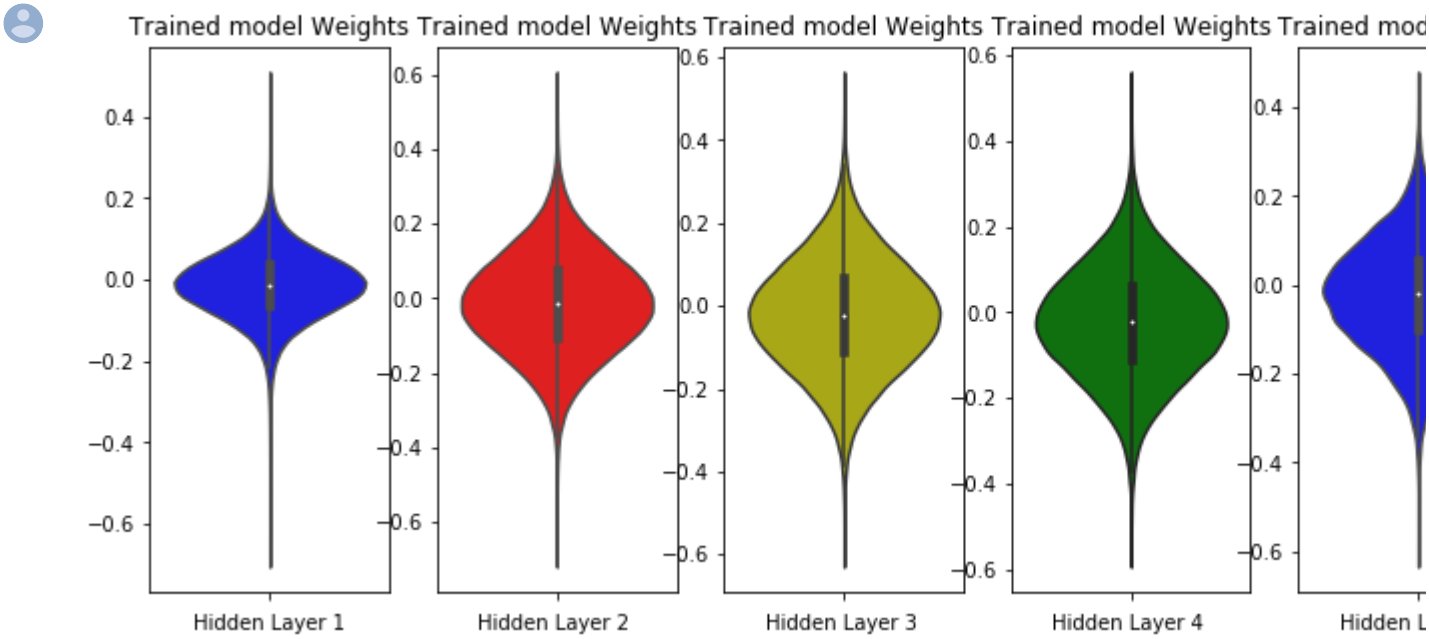
```
fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')
# list of epoch numbers
x = list(range(1,nb_epoch+1))
# print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=
# we will get val_loss and val_acc only when you pass the paramter validation_data
# val_loss : validation loss
# val_acc : validation accuracy
# loss : training loss
# acc : train accuracy
# for each key in histrory.histrory we will have a list of length equal to number of epochs
vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
```

```
Train score: 0.06144777707796311
Train accuracy: 98.44166666666668

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

Test score: 0.11881388411391526
Test accuracy: 97.36
```




```
w_after = model_relu.get_weights()
h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
h3_w = w_after[4].flatten().reshape(-1,1)
h4_w = w_after[6].flatten().reshape(-1,1)
h5_w = w_after[8].flatten().reshape(-1,1)
out_w = w_after[10].flatten().reshape(-1,1)
fig = plt.figure(figsize=(15,5))
plt.title("Weight matrices after model trained")

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

```
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

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

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

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

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

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



4. MLP + ReLU + adam + dropout + batch_normalization

```
# Multilayer perceptron
# https://arxiv.org/pdf/1707.09725.pdf#page=95
# for relu layers
# If we sample weights from a normal distribution N(0,σ) we satisfy this condition with σ=√(2
# h1 => σ=√(2/(fan_in) = 0.062 => N(0,σ) = N(0,0.062)
# h2 => σ=√(2/(fan_in) = 0.125 => N(0,σ) = N(0,0.125)
# out => σ=√(2/(fan_in+1) = 0.120 => N(0,σ) = N(0,0.120)
model_relu = Sequential()
model_relu.add(Dense(690, activation='relu', input_shape=(input_dim,), kernel_initializer=Ran
model_relu.add(BatchNormalization())
model_relu.add(Dropout(0.5))
model_relu.add(Dense(530, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev
model_relu.add(BatchNormalization())
model_relu.add(Dropout(0.5))
model_relu.add(Dense(412, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev
model_relu.add(BatchNormalization())
model_relu.add(Dropout(0.5))
model_relu.add(Dense(231, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev
model_relu.add(BatchNormalization())
model_relu.add(Dropout(0.5))
model_relu.add(Dense(112, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev
model_relu.add(BatchNormalization())
model_relu.add(Dropout(0.5))
model_relu.add(Dense(output_dim, activation='softmax'))
model_relu.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_47 (Dense)             (None, 690)               541650    
_________________________________________________________________
batch_normalization_16 (Batc (None, 690)               2760      
_________________________________________________________________
dropout_16 (Dropout)         (None, 690)               0         
_________________________________________________________________
dense_48 (Dense)             (None, 530)               366230    
_________________________________________________________________
batch_normalization_17 (Batc (None, 530)               2120      
_________________________________________________________________
dropout_17 (Dropout)         (None, 530)               0         
_________________________________________________________________
dense_49 (Dense)             (None, 412)               218772    
_________________________________________________________________
batch_normalization_18 (Batc (None, 412)               1648      
_________________________________________________________________
dropout_18 (Dropout)         (None, 412)               0         
_________________________________________________________________
dense_50 (Dense)             (None, 231)               95403     
_________________________________________________________________
batch_normalization_19 (Batc (None, 231)               924       
_________________________________________________________________
dropout_19 (Dropout)         (None, 231)               0         
_________________________________________________________________
dense_51 (Dense)             (None, 112)               25984     
_________________________________________________________________
batch_normalization_20 (Batc (None, 112)               448       
_________________________________________________________________
dropout_20 (Dropout)         (None, 112)               0         
_________________________________________________________________
dense_52 (Dense)             (None, 10)                1130      
=================================================================
Total params: 1,257,069
Trainable params: 1,253,119
Non-trainable params: 3,950
_________________________________________________________________
```

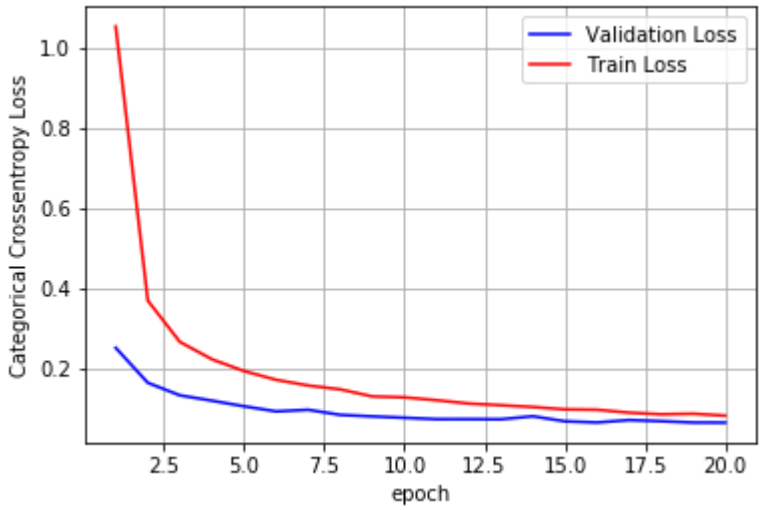
```
model_relu.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
history = model_relu.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1,
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 26s 428us/step - loss: 1.0527 - acc: 0.66
Epoch 2/20
60000/60000 [==============================] - 21s 357us/step - loss: 0.3679 - acc: 0.89
Epoch 3/20
60000/60000 [==============================] - 24s 406us/step - loss: 0.2647 - acc: 0.92
Epoch 4/20
60000/60000 [==============================] - 24s 404us/step - loss: 0.2213 - acc: 0.93
Epoch 5/20
60000/60000 [==============================] - 23s 385us/step - loss: 0.1919 - acc: 0.94
Epoch 6/20
60000/60000 [==============================] - 24s 407us/step - loss: 0.1700 - acc: 0.95
Epoch 7/20
60000/60000 [==============================] - 22s 375us/step - loss: 0.1557 - acc: 0.95
Epoch 8/20
60000/60000 [==============================] - 21s 346us/step - loss: 0.1461 - acc: 0.95
Epoch 9/20
60000/60000 [==============================] - 21s 353us/step - loss: 0.1285 - acc: 0.96
Epoch 10/20
60000/60000 [==============================] - 21s 356us/step - loss: 0.1262 - acc: 0.96
Epoch 11/20
60000/60000 [==============================] - 23s 391us/step - loss: 0.1190 - acc: 0.96
Epoch 12/20
60000/60000 [==============================] - 25s 414us/step - loss: 0.1107 - acc: 0.96
Epoch 13/20
60000/60000 [==============================] - 20s 333us/step - loss: 0.1066 - acc: 0.97
Epoch 14/20
60000/60000 [==============================] - 22s 365us/step - loss: 0.1021 - acc: 0.97
Epoch 15/20
60000/60000 [==============================] - 20s 341us/step - loss: 0.0961 - acc: 0.97
Epoch 16/20
60000/60000 [==============================] - 25s 412us/step - loss: 0.0952 - acc: 0.97
Epoch 17/20
60000/60000 [==============================] - 24s 398us/step - loss: 0.0879 - acc: 0.97
Epoch 18/20
60000/60000 [==============================] - 20s 335us/step - loss: 0.0839 - acc: 0.97
Epoch 19/20
60000/60000 [==============================] - 20s 337us/step - loss: 0.0853 - acc: 0.97
Epoch 20/20
60000/60000 [==============================] - 20s 341us/step - loss: 0.0804 - acc: 0.97
```

```
#Evualate your model with accuracy and plot of (NUmber of epoches VS train_and_val_loss)
#Train accuracy
score = model_relu.evaluate(X_train, Y_train, verbose=0)
print('Train score:', score[0])
print('Train accuracy:', score[1]*100)
print('\n********************** *********************\n')
#test accuracy
score = model_relu.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1]*100)
fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')
```

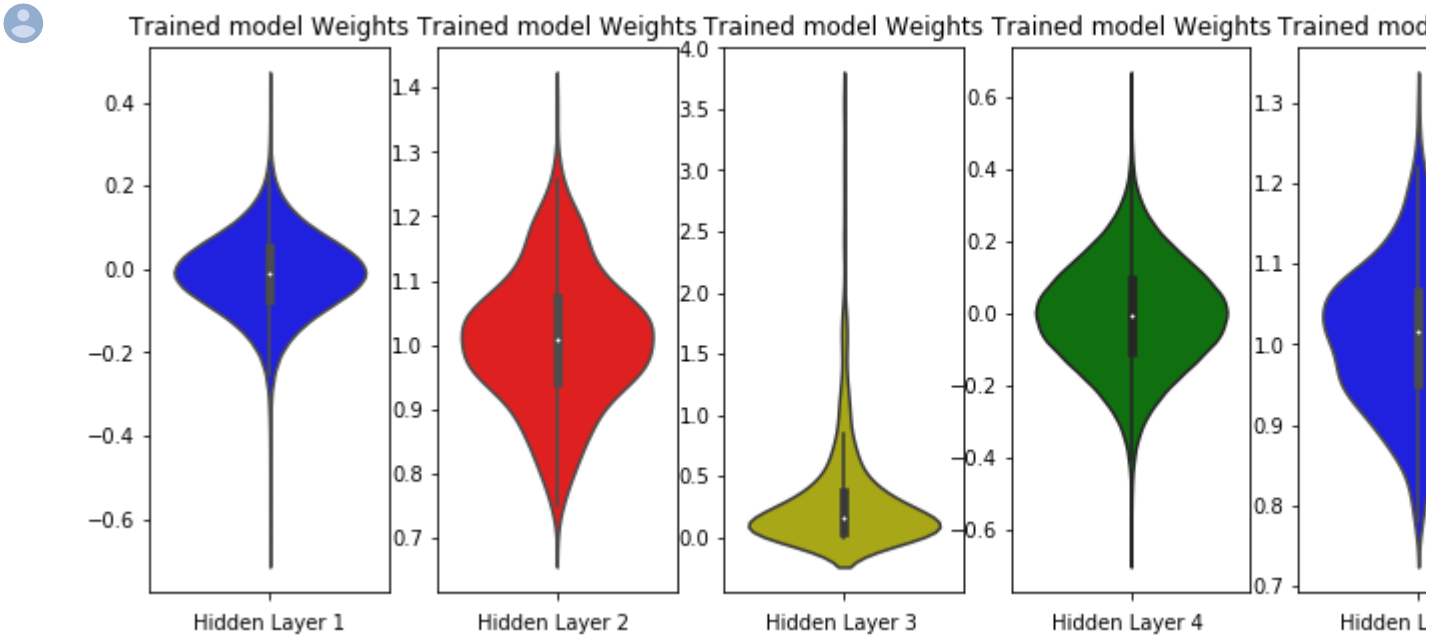
```
# list of epoch numbers
x = list(range(1,nb_epoch+1))
# print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=
# we will get val_loss and val_acc only when you pass the paramter validation_data
# val_loss : validation loss
# val_acc : validation accuracy
# loss : training loss
# acc : train accuracy
# for each key in histrory.histrory we will have a list of length equal to number of epochs
vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
```

```
Train score: 0.019241652972002823
Train accuracy: 99.47833333333334

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

Test score: 0.06302054594261572
Test accuracy: 98.3
```




```
w_after = model_relu.get_weights()
h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[2].flatten().reshape(-1,1)
h3_w = w_after[4].flatten().reshape(-1,1)
h4_w = w_after[6].flatten().reshape(-1,1)
h5_w = w_after[8].flatten().reshape(-1,1)
out_w = w_after[10].flatten().reshape(-1,1)
fig = plt.figure(figsize=(15,5))
plt.title("Weight matrices after model trained")

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

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

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

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

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

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



CONCLUSION:

```
from prettytable import PrettyTable
tb = PrettyTable()
```

```
tb.field_names= ("Hidden Layers", "Model", "Accuracy")
tb.add_row(["2", "MLP + ADAM + RELU",97.82])
tb.add_row(["2", "MLP + ADAM + RELU + batch_normalization",98.2])
tb.add_row(["2", "MLP + ADAM + RELU + dropout",97.77])
tb.add_row(["2", "MLP + ADAM + RELU + dropout+ batch_normalization",98.19])
tb.add_row([" ", " "," "])
tb.add_row([" ", " "," "])
tb.field_names= ("Hidden Layers", "Model", "Accuracy")
tb.add_row(["3", "MLP + ADAM + RELU",97.99])
tb.add_row(["3", "MLP + ADAM + RELU + batch_normalization",98.03])
tb.add_row(["3", "MLP + ADAM + RELU + dropout",83.14])
tb.add_row(["3", "MLP + ADAM + RELU + dropout+ batch_normalization",98.21])
tb.add_row([" ", " "," "])
tb.add_row([" ", " "," "])
tb.field_names= ("Hidden Layers", "Model", "Accuracy")
tb.add_row(["5", "MLP + ADAM + RELU",98.02])
tb.add_row(["5", "MLP + ADAM + RELU + batch_normalization",98.34])
tb.add_row(["5", "MLP + ADAM + RELU + dropout",97.36])
tb.add_row(["5", "MLP + ADAM + RELU + dropout+ batch_normalization",98.3])
print(tb.get_string(titles = "MLP Models - Observations"))
```

```
+---------------+-----------------------------------------------------+----------+
| Hidden Layers |                        Model                        | Accuracy |
+---------------+-----------------------------------------------------+----------+
|       2       |                  MLP + ADAM + RELU                  |  97.82   |
|       2       |      MLP + ADAM + RELU + batch_normalization        |   98.2   |
|       2       |             MLP + ADAM + RELU + dropout             |  97.77   |
|       2       | MLP + ADAM + RELU + dropout+ batch_normalization    |  98.19   |
|               |                                                     |          |
|               |                                                     |          |
|       3       |                  MLP + ADAM + RELU                  |  97.99   |
|       3       |      MLP + ADAM + RELU + batch_normalization        |  98.03   |
|       3       |             MLP + ADAM + RELU + dropout             |  83.14   |
|       3       | MLP + ADAM + RELU + dropout+ batch_normalization    |  98.21   |
|               |                                                     |          |
|               |                                                     |          |
|       5       |                  MLP + ADAM + RELU                  |  98.02   |
|       5       |      MLP + ADAM + RELU + batch_normalization        |  98.34   |
|       5       |             MLP + ADAM + RELU + dropout             |  97.36   |
|       5       | MLP + ADAM + RELU + dropout+ batch_normalization    |   98.3   |
+---------------+-----------------------------------------------------+----------+
```