```
1 # Credits: https://github.com/keras-team/keras/blob/master/examples/mnist_cnn.py
 3
%matplotlib inline
4 import matplotlib.pyplot as plt
5 import seaborn as sns
 import warnings
warnings.filterwarnings("ignore")
10 from __future__ import print_function import keras
10 from
12 from keras.datasets import mnist
 13 from keras.models import Sequential
14 from keras.layers import Dense, Dropout, Flatten
15 from keras.layers import Conv2D, MaxPooling2D
 16 from keras import backend as K
18 batch_size = 128
19 num_classes = 10
20 epochs = 10
22 # input image dimensions
23 img_rows, img_cols = 28, 28
25 # the data, split between train and test sets
26 (x_train, y_train), (x_test, y_test) = mnist.load_data()
28
29 if K.image_data_format() == 'channels_first'
           x_train = x_train.reshape(x_train.shape[0], 1, img_rows, img_cols)
x_test = x_test.reshape(x_test.shape[0], 1, img_rows, img_cols)
30
31
           input_shape = (1, img_rows, img_cols)
33 else:
          x_train = x_train.reshape(x_train.shape[0], img_rows, img_cols, 1)
x_test = x_test.reshape(x_test.shape[0], img_rows, img_cols, 1)
input_shape = (img_rows, img_cols, 1)
35
38  x_train = x_train.astype('float32')
39  x_test = x_test.astype('float32')
40  x_train /= 255
41  x_test /= 255
42 print('x_train shape:', x_train.shape)
43 print(x_train.shape[0], 'train samples')
44 print(x_test.shape[0], 'test samples')
46 # convert class vectors to binary class matrices
47 y_train = keras.utils.to_categorical(y_train, num_classes)
48 y_test = keras.utils.to_categorical(y_test, num_classes)

    x_train shape: (60000, 28, 28, 1)

      60000 train samples
      10000 test samples
 1 import numpy as np
  2 import time
 # https://gist.github.com/greydanus/f6eee59eaf1d90fcb3b534a25362cea4
# https://stackoverflow.com/a/14434334
 # https://stackwolentow.com/a/1443334
# this function is used to update the plots for each epoch and error
def plt_dynamic(x, vy, fig, ax, colors=['b']):
ax.plot(x, vy, 'b', label="Validation Loss")
ax.plot(x, ty, 'r', label="Train Loss")
          plt.legend()
           plt.grid()
11
          fig.canvas.draw()
  1 def loss plot(model name):
          score = model_name.evaluate(x_test, y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])
          fig, ax = plt.subplots(1,1, figsize=(10,6))
ax.set_xlabel('epoch'); ax.set_ylabel('Categorical Crossentropy Loss')
ax.set_title('Variation of Loss with epochs')
          # list of epoch numbers
          x = list(range(1,epochs+1))
          # print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, validation_data=(X_test, Y_test))
13
14
          # we will get val_loss and val_acc only when you pass the paramter validation_data
# val_loss : validation loss
# val_acc : validation accuracy
18
19
21
           # loss : training loss
           # acc : train accurac
23
           # for each key in histrory.histrory we will have a list of length equal to number of epochs
24
          vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, fig, ax)
26
27
 1 def weight_plot(model_name):
          w_after = model_name.get_weights()
           h1_w = w_after[0].flatten().reshape(-1,1)
```

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

fig = plt.figure(figsize=(15,7))
fig.suptitle("Weight matrices after model trained")
plt.subplot(1, 3, 1)
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')

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

plt.subplot(1, 3, 3)
ax = sns.violinplot(y=out_w,color='y')
plt.subplot(1, 3, 3)
ax = sns.violinplot(y=out_w,color='y')
plt.show()
```

▼ Architecture 1:

no. of Layers = 3; Kernel_size = 3x3

₽

Model: "sequential_5"

Layer (type)	Output	Shape	Param #
conv2d_18 (Conv2D)	(None,	26, 26, 48)	480
conv2d_19 (Conv2D)	(None,	24, 24, 64)	27712
max_pooling2d_14 (MaxPooling	(None,	12, 12, 64)	0
dropout_16 (Dropout)	(None,	12, 12, 64)	0
conv2d_20 (Conv2D)	(None,	10, 10, 50)	28850
max_pooling2d_15 (MaxPooling	(None,	5, 5, 50)	0
dropout_17 (Dropout)	(None,	5, 5, 50)	0
flatten_4 (Flatten)	(None,	1250)	0
dense_7 (Dense)	(None,	128)	160128
dropout_18 (Dropout)	(None,	128)	0
dense_8 (Dense)	(None,	10)	1290
Total params: 218,460 Trainable params: 218,460 Non-trainable params: 0	=====		======

None

Train on 60000 samples, validate on 10000 samples

Epoch 1/10

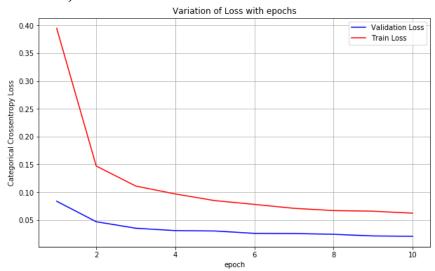
```
6000/60000 [============] - 5s 88us/step - loss: 0.3946 - acc: 0.8724 - val_loss: 0.0837 - val_acc: 0.9743
Epoch 2/10
Epoch 3/10
60000/60000 [================] - 4s 72us/step - loss: 0.1110 - acc: 0.9662 - val_loss: 0.0352 - val_acc: 0.9877
Epoch 4/10
60000/60000 [============] - 4s 72us/step - loss: 0.0968 - acc: 0.9710 - val loss: 0.0309 - val acc: 0.9887
Epoch 5/10
60000/60000 [==============] - 4s 72us/step - loss: 0.0848 - acc: 0.9741 - val_loss: 0.0302 - val_acc: 0.9901
Epoch 6/10
60000/60000 [
          Epoch 7/10
6000/60000 [=============== ] - 4s 72us/step - loss: 0.0710 - acc: 0.9791 - val_loss: 0.0257 - val_acc: 0.9910
Epoch 8/10
Epoch 9/10
60000/60000 [============] - 4s 72us/step - loss: 0.0658 - acc: 0.9804 - val_loss: 0.0214 - val_acc: 0.9940
Epoch 10/10
60000/60000 [===========] - 4s 72us/step - loss: 0.0623 - acc: 0.9818 - val_loss: 0.0207 - val_acc: 0.9935
```

¹ loss_plot(model1)

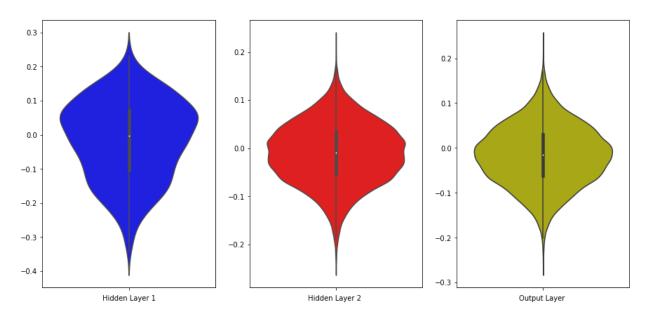
² weight_plot(model1)

Test score: 0.02070148353522236

Test accuracy: 0.9935



Weight matrices after model trained



▼ Architecture 2:

no. of Layers = 5; Kernel_size = 5x5

```
optimizer=keras.optimizers.Adadelta(),
metrics=['accuracy'])
history = model2.fit(x_train, y_train, batch_size=batch_size, epochs=epochs, verbose=1, validation_data=(x_test, y_test))

33
history = model2.fit(x_train, y_train, batch_size=batch_size, epochs=epochs, verbose=1, validation_data=(x_test, y_test))
```

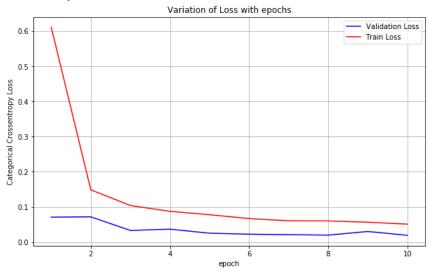
```
Layer (type)
               Output Shape
                             Param #
conv2d_70 (Conv2D)
               (None, 28, 28, 50)
                             1300
                             62550
conv2d_71 (Conv2D)
               (None, 28, 28, 50)
max_pooling2d_55 (MaxPooling (None, 14, 14, 50)
                             a
dropout_70 (Dropout)
               (None, 14, 14, 50)
                             0
conv2d_72 (Conv2D)
               (None, 14, 14, 60)
                             75060
dropout_71 (Dropout)
               (None, 14, 14, 60)
                             0
conv2d_73 (Conv2D)
               (None, 14, 14, 40)
                             60040
max_pooling2d_56 (MaxPooling (None, 5, 5, 40)
                             0
dropout_72 (Dropout)
               (None, 5, 5, 40)
                             0
conv2d_74 (Conv2D)
               (None, 5, 5, 30)
                             30030
                             0
dropout_73 (Dropout)
               (None, 5, 5, 30)
flatten_12 (Flatten)
               (None, 750)
                             0
dense_23 (Dense)
               (None, 128)
                             96128
dropout_74 (Dropout)
                             0
               (None, 128)
dense_24 (Dense)
               (None, 10)
                             1290
Total params: 326,398
Trainable params: 326,398
Non-trainable params: 0
None
Train on 60000 samples, validate on 10000 samples
Epoch 1/10
       60000/60000 [
Epoch 2/10
60000/60000 [
        Epoch 3/10
60000/60000 [
         Epoch 4/10
       60000/60000 [
Epoch 5/10
60000/60000 [
           Epoch 6/10
60000/60000 [============] - 7s 113us/step - loss: 0.0669 - acc: 0.9810 - val_loss: 0.0226 - val_acc: 0.993
Epoch 7/10
60000/60000 [
        Epoch 8/10
60000/60000 [
          Epoch 9/10
60000/60000 [
       Epoch 10/10
```

```
1 loss_plot(model2)
```

₽

Test score: 0.019397488478862943

Test accuracy: 0.994



▼ Architecture 3:

no. of Layers = 7; Kernel_size = 6x6

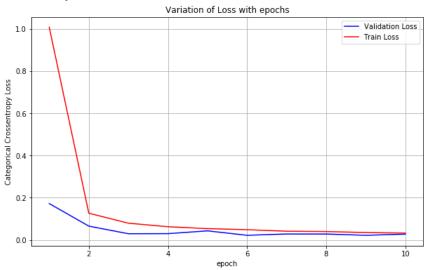
along with Batch Normalization and Dropout layers

```
1 from keras.layers.normalization import BatchNormalization
 3 model3 = Sequential()
    #Layer 1
 #Layer 2
model3.add(Conv2D(80, (6, 6), padding='same', activation='relu'))
model3.add(BatchNormalization())
model3.add(MaxPooling2D(pool_size=(2, 2), padding='same'))
model3.add(Dropout(0.5))
15
16 #Layer 3
17 model3.add(Conv2D(60, (6, 6), padding='same', activation='relu'))
18 model3.add(BatchNormalization())
19 model3.add(Dropout(0.5))
20
21 #Layer 4
#Idde: 4
#Idde: 4
model3.add(Conv2D(50, (6, 6), padding='same', activation='relu'))
model3.add(BatchNormalization())
description
model3.add(MaxPooling2D(pool_size=(2, 2), padding='same'))
25 model3.add(Dropout(0.5))
26
27 #Layer 5
model3.add(Conv2D(48, (6, 6), padding='same', activation='relu'))
model3.add(BatchNormalization())
30 model3.add(Dropout(0.5))
31
32 #Layer 6
33 model3.add(Conv2D(36, (6, 6), padding='same', activation='relu'))
34 model3.add(BatchNormalization())
35 model3.add(Dropout(0.5))
36
37 #Layer 7
model3.add(Conv2D(24, (6, 6), padding='same', activation='relu'))
model3.add(BatchNormalization())
model3.add(MaxPooling2D(pool_size=(2, 2), padding='same'))
41 model3.add(Dropout(0.5))
42
43 model3.add(Flatten())
44 model3.add(Dense(128, activation='relu'))
45 model3.add(Dropout(0.5))
46 model3.add(Dense(num_classes, activation='softmax'))
48 print(model3.summary())
50 model3.compile(loss=keras.losses.categorical_crossentropy,
                        optimizer=keras.optimizers.Adadelta(),
metrics=['accuracy'])
52
history = model3.fit(x_train, y_train, batch_size=batch_size, epochs=epochs, verbose=1, validation_data=(x_test, y_test))
```

Layer (type)	Output Shape	Param #		
conv2d_63 (Conv2D)	(None, 28, 28, 70)	2590		
batch_normalization_49 (Batc	(None, 28, 28, 70)	280		
conv2d_64 (Conv2D)	(None, 28, 28, 80)	201680		
batch_normalization_50 (Batc	(None, 28, 28, 80)	320		
max_pooling2d_52 (MaxPooling	(None, 14, 14, 80)	0		
dropout_63 (Dropout)	(None, 14, 14, 80)	0		
conv2d_65 (Conv2D)	(None, 14, 14, 60)	172860		
batch_normalization_51 (Batc	(None, 14, 14, 60)	240		
dropout_64 (Dropout)	(None, 14, 14, 60)	0		
conv2d_66 (Conv2D)	(None, 14, 14, 50)	108050		
batch_normalization_52 (Batc	(None, 14, 14, 50)	200		
max_pooling2d_53 (MaxPooling	(None, 7, 7, 50)	0		
dropout_65 (Dropout)	(None, 7, 7, 50)	0		
conv2d_67 (Conv2D)	(None, 7, 7, 48)	86448		
batch_normalization_53 (Batc	(None, 7, 7, 48)	192		
dropout_66 (Dropout)	(None, 7, 7, 48)	0		
conv2d_68 (Conv2D)	(None, 7, 7, 36)	62244		
batch_normalization_54 (Batc	(None, 7, 7, 36)	144		
dropout_67 (Dropout)	(None, 7, 7, 36)	0		
conv2d_69 (Conv2D)	(None, 7, 7, 24)	31128		
batch_normalization_55 (Batc	(None, 7, 7, 24)	96		
max_pooling2d_54 (MaxPooling	(None, 4, 4, 24)	0		
dropout_68 (Dropout)	(None, 4, 4, 24)	0		
flatten_11 (Flatten)	(None, 384)	0		
dense_21 (Dense)	(None, 128)	49280		
dropout_69 (Dropout)	(None, 128)	0		
dense_22 (Dense)	(None, 10)	1290		
Total params: 717,042 Trainable params: 716,306				
Non-trainable params: 736				
None Train on 60000 samples, vali	date on 10000 samples			
Epoch 1/10 60000/60000 [==========	•	384us/sten - 1	oss: 1.0074 - acc	0.6573 -
Epoch 2/10 60000/60000 [=======	-			
Epoch 3/10 60000/60000 [=======	-	•		
Epoch 4/10 60000/60000 [===========	-			
Epoch 5/10 60000/60000 [=======	-			
Epoch 6/10 60000/60000 [========	-	•		
Epoch 7/10 60000/60000 [========	-			
Epoch 8/10 60000/60000 [========	-	•		
Epoch 9/10 60000/60000 [========	-			
Epoch 10/10 60000/60000 [=======	-			_
		23002/216b - 1	133. 0.0320 - dCC:	0.3314 - Val_109

Test score: 0.02765477129972496

Test accuracy: 0.9945



▼ Summary

```
# Please compare all your models using Prettytable library
from prettytable import PrettyTable
x = PrettyTable()
print('\nResults : CNN on MNIST data')
print(40*'=')

x.field_names = ["Hidden layers", "Kernel size", "Padding", "Max pooling", "epochs", "Train error", "Train accuracey", "Test error", "Te
x.add_row([3, '3X3', 'valid', '(2,2)', 10, 0.0623, '98.18 %', 0.0207, '99.35 %'])
x.add_row([5, '5X5', 'same', '(2,2)', 10, 0.0511, '98.60 %', 0.0194, '99.40 %'])
x.add_row([7, '6X6', 'same', '(2,2)', 10, 0.0326, '99.14 %', 0.0277, '99.45 %'])
print(x)
```

Results : CNN on MNIST data

+ Hidden layers	+ Kernel size	+ Padding	+ Max pooling	+ epochs	+ Train error	+ Train accuracey	Test error	+ Test accuracy
3	3X3	valid	(2,2)	10	0.0623	98.18 %	0.0207	99.35 %
5	5X5	same	(2,2)	10	0.0511	98.60 %	0.0194	99.40 %
7	6X6	same	(2,2)	10	0.0326	99.14 %	0.0277	99.45 %