

```
In [1]: # if you keras is not using tensorflow as backend set "KERAS_BACKEND=tensorflow"
from keras.utils import np_utils
from keras.datasets import mnist
import seaborn as sns
from keras.initializers import RandomNormal
```

Using TensorFlow backend.

The default version of TensorFlow in Colab will soon switch to TensorFlow 2.x.

We recommend you [upgrade](https://www.tensorflow.org/guide/migrate) (https://www.tensorflow.org/guide/migrate) now or ensure your notebook will continue to use TensorFlow 1.x via the %tensorflow_version 1.x magic: [more info](https://colab.research.google.com/notebooks/tensorflow_version.ipynb) (https://colab.research.google.com/notebooks/tensorflow_version.ipynb).

```
In [0]: %matplotlib notebook
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()
```

```
In [3]: # 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 (https://s3.amazonaws.com/img-datasets/mnist.npz)
11493376/11490434 [=====] - 1s 0us/step

```
In [4]: print("Number of training examples :", X_train.shape[0], "and each image is of shape", X_train.shape[1]*X_train.shape[2])
print("Number of training examples :", X_test.shape[0], "and each image is of shape", X_test.shape[1]*X_test.shape[2])
```

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

```
In [0]: # if you observe the input shape its 2 dimensional 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])
```

In [6]: *# 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 (784)")
print("Number of training examples :", X_test.shape[0], "and each image is of shape (784)")
```

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

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

In [7]: *# An example data point*

```
print(X_train[0])
```

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

```
In [0]: # 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
#  $X \Rightarrow (X - X_{min}) / (X_{max} - X_{min}) = X / 255$ 

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

```
In [9]: # example data point after normalizing
print(X_train[0])
```

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

```
In [10]: # here we are having a class number for each image
print("Class label of first image :", y_train[0])

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

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

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

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

```
In [0]: from keras.models import Sequential
from keras.layers import Dense, Activation
```

```
In [0]: # some model parameters

output_dim = 10
input_dim = X_train.shape[1]

batch_size = 128
nb_epoch = 20
```

Type-I MLP_RelU_Adam_2Layer_1024_64

```
In [15]: # https://stackoverflow.com/questions/34716454/where-do-i-call-the-batchnormalization-layer-in-keras

from keras.layers import Dropout
from keras.layers.normalization import BatchNormalization

model_drop = Sequential()

model_drop.add(Dense(1024, activation='relu', input_shape=(input_dim,)), kernel_initializer=RandomNormal(mean=0, stddev=0.01))
# model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

model_drop.add(Dense(64, activation='relu', kernel_initializer=RandomNormal(mean=0, stddev=0.01)))
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

model_drop.add(Dense(output_dim, activation='softmax'))

# print(model_drop.summary())

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

history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epochs, validation_data=(X_val, Y_val))

model_drop.summary()
```

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/tensorflow_core/python/ops/math_grad.py:1424: where (from tensorflow.python.ops.array_ops) is deprecated and will be removed in a future version.

Instructions for updating:

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

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:1033: The name tf.assign_add is deprecated. Please use tf.compat.v1.assign_add instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:1020: The name tf.assign is deprecated. Please use tf.compat.v1.assign instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:3005: The name tf.Session is deprecated. Please use tf.compat.v1.Session instead.

Train on 60000 samples, validate on 10000 samples

Epoch 1/20

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:190: The name tf.get_default_session is deprecated. Please use tf.compat.v1.get_default_session instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:197: The name tf.ConfigProto is deprecated. Please use tf.compat.v1.ConfigProto instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:207: The name tf.global_variables is deprecated. Please use tf.compat.v1.global_variables instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:216: The name tf.is_variable_initialized is deprecated. Please use tf.compat.v1.is_variable_initialized instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:223: The name tf.variables_initializer is deprecated. Please use tf.compat.v1.variables_initializer instead.

```
60000/60000 [=====] - 15s 248us/step - loss: 0.5077 -  
acc: 0.8482 - val_loss: 0.1529 - val_acc: 0.9554  
Epoch 2/20  
60000/60000 [=====] - 14s 233us/step - loss: 0.2440 -  
acc: 0.9279 - val_loss: 0.1150 - val_acc: 0.9644  
Epoch 3/20  
60000/60000 [=====] - 14s 234us/step - loss: 0.1868 -  
acc: 0.9450 - val_loss: 0.0933 - val_acc: 0.9700  
Epoch 4/20  
60000/60000 [=====] - 14s 230us/step - loss: 0.1617 -  
acc: 0.9528 - val_loss: 0.0907 - val_acc: 0.9739  
Epoch 5/20  
60000/60000 [=====] - 15s 243us/step - loss: 0.1422 -  
acc: 0.9581 - val_loss: 0.0852 - val_acc: 0.9737  
Epoch 6/20  
60000/60000 [=====] - 14s 234us/step - loss: 0.1256 -  
acc: 0.9631 - val_loss: 0.0749 - val_acc: 0.9782  
Epoch 7/20  
60000/60000 [=====] - 14s 241us/step - loss: 0.1128 -  
acc: 0.9667 - val_loss: 0.0750 - val_acc: 0.9775  
Epoch 8/20  
60000/60000 [=====] - 15s 251us/step - loss: 0.1051 -  
acc: 0.9690 - val_loss: 0.0719 - val_acc: 0.9790  
Epoch 9/20  
60000/60000 [=====] - 14s 231us/step - loss: 0.1005 -  
acc: 0.9702 - val_loss: 0.0670 - val_acc: 0.9801  
Epoch 10/20  
60000/60000 [=====] - 14s 228us/step - loss: 0.0908 -  
acc: 0.9717 - val_loss: 0.0624 - val_acc: 0.9817  
Epoch 11/20  
60000/60000 [=====] - 14s 231us/step - loss: 0.0869 -  
acc: 0.9741 - val_loss: 0.0623 - val_acc: 0.9832  
Epoch 12/20  
60000/60000 [=====] - 14s 231us/step - loss: 0.0758 -  
acc: 0.9771 - val_loss: 0.0609 - val_acc: 0.9816  
Epoch 13/20  
60000/60000 [=====] - 14s 230us/step - loss: 0.0744 -  
acc: 0.9770 - val_loss: 0.0618 - val_acc: 0.9829  
Epoch 14/20  
60000/60000 [=====] - 14s 227us/step - loss: 0.0725 -  
acc: 0.9778 - val_loss: 0.0604 - val_acc: 0.9830  
Epoch 15/20  
60000/60000 [=====] - 14s 236us/step - loss: 0.0663 -  
acc: 0.9801 - val_loss: 0.0585 - val_acc: 0.9835  
Epoch 16/20  
60000/60000 [=====] - 14s 231us/step - loss: 0.0622 -  
acc: 0.9809 - val_loss: 0.0609 - val_acc: 0.9828  
Epoch 17/20  
60000/60000 [=====] - 14s 228us/step - loss: 0.0593 -
```

acc: 0.9823 - val_loss: 0.0595 - val_acc: 0.9845

Epoch 18/20

60000/60000 [=====] - 14s 231us/step - loss: 0.0583 -

acc: 0.9823 - val_loss: 0.0631 - val_acc: 0.9832

Epoch 19/20

60000/60000 [=====] - 14s 228us/step - loss: 0.0550 -

acc: 0.9831 - val_loss: 0.0607 - val_acc: 0.9835

Epoch 20/20

60000/60000 [=====] - 13s 225us/step - loss: 0.0533 -

acc: 0.9834 - val_loss: 0.0570 - val_acc: 0.9845

Model: "sequential_3"

Layer (type)	Output Shape	Param #
=====		
dense_6 (Dense)	(None, 1024)	803840
dropout_4 (Dropout)	(None, 1024)	0
dense_7 (Dense)	(None, 64)	65600
batch_normalization_2 (Batch Normalization)	(None, 64)	256
dropout_5 (Dropout)	(None, 64)	0
dense_8 (Dense)	(None, 10)	650
=====		
Total params: 870,346		
Trainable params: 870,218		
Non-trainable params: 128		

Accuracy

```

In [51]: score = model_drop.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

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

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

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

# 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 history.history we will have a list of length equal to number of epochs

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

```

Test score: 0.09080233381008729

Test accuracy: 0.9804

<IPython.core.display.Javascript object>

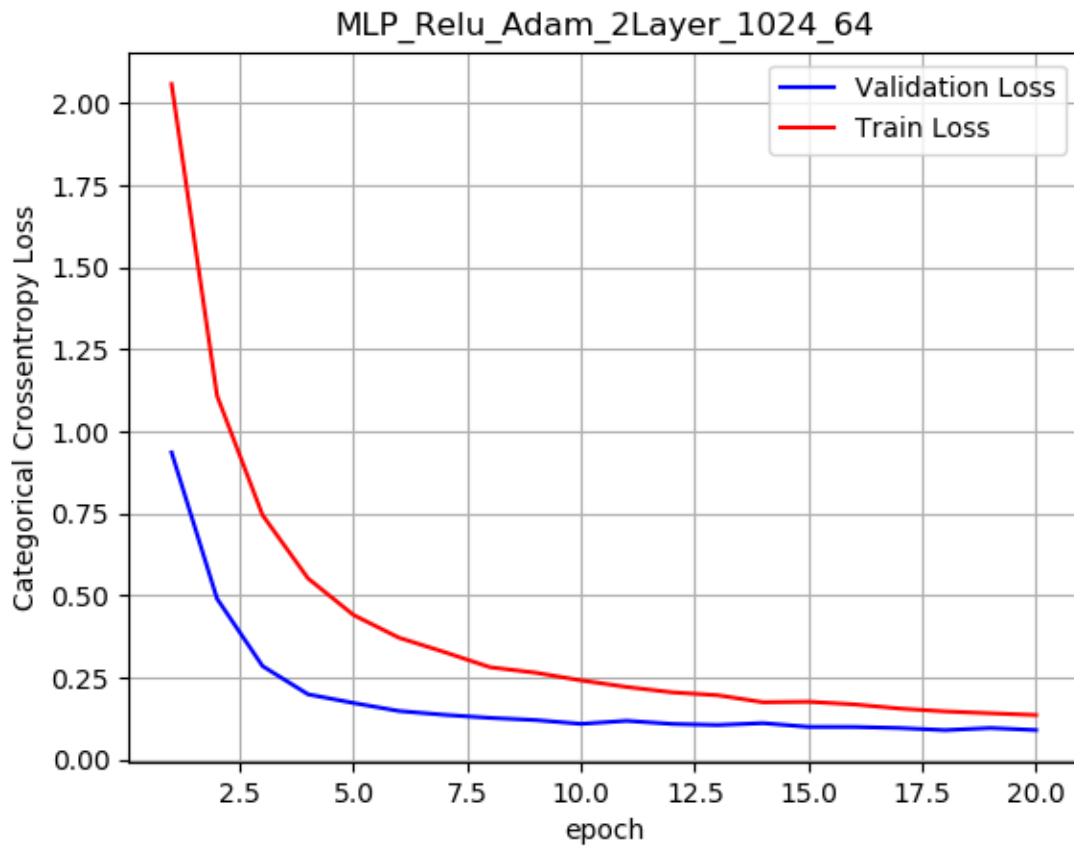
```

[1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20]
[0.9364621857643127, 0.49075753841400144, 0.2855819786310196, 0.199641513609886
16, 0.17320310388207436, 0.14879324183166026, 0.1371548559397459, 0.12790572729
706765, 0.12123643999770284, 0.10966003392711282, 0.11899310316890478, 0.109499
49248600752, 0.10622592614218593, 0.11184748293552547, 0.10049898426607251, 0.1
0034355153460056, 0.09705943623417988, 0.09053028036076576, 0.0970813074545003
5, 0.09080233482245821]
[2.058573489634196, 1.1087739948590596, 0.7454398405392965, 0.5526444519678751,
0.44117149138450623, 0.37196457761128743, 0.32815683867136636, 0.28217501312891
64, 0.26549448329607644, 0.24212648111979165, 0.22209778400262198, 0.2057082060
8933768, 0.1968686815738678, 0.1755473879337311, 0.1770206745068232, 0.16906047
227780024, 0.15631902202765147, 0.14764749088684717, 0.14192116012970607, 0.136
5976075251897]

```



```
In [3]: %matplotlib notebook
import matplotlib.pyplot as plt
import numpy as np
import time
fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch') ;
ax.set_ylabel('Categorical Crossentropy Loss')
ax.set_title(label="MLP_ReLU_Adam_2Layer_1024_64")
plt_dynamic(x, vy, ty, ax)
```



Type-II MLP_ReLU_Adam_3Layer_512_128_64

```
In [25]: # https://stackoverflow.com/questions/34716454/where-do-i-call-the-batchnormalization-layer
from keras.layers import Dropout

model_drop = Sequential()

model_drop.add(Dense(512, activation='relu', input_shape=(input_dim,), kernel_initializer=RandomNormal(mean=0.0, stddev=0.01)))
# model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

model_drop.add(Dense(128, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.01)))
# model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

model_drop.add(Dense(64, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.01)))
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

model_drop.add(Dense(output_dim, activation='softmax'))

# print(model_drop.summary())

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

history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epochs)

model_drop.summary()
```

Train on 60000 samples, validate on 10000 samples

Epoch 1/20

60000/60000 [=====] - 10s 162us/step - loss: 1.0693 - acc: 0.6588 - val_loss: 0.2757 - val_acc: 0.9233

Epoch 2/20

60000/60000 [=====] - 9s 143us/step - loss: 0.4742 - acc: 0.8602 - val_loss: 0.1845 - val_acc: 0.9446

Epoch 3/20

60000/60000 [=====] - 9s 150us/step - loss: 0.3542 - acc: 0.8994 - val_loss: 0.1449 - val_acc: 0.9573

Epoch 4/20

60000/60000 [=====] - 9s 146us/step - loss: 0.2920 - acc: 0.9179 - val_loss: 0.1317 - val_acc: 0.9612

Epoch 5/20

60000/60000 [=====] - 9s 143us/step - loss: 0.2549 - acc: 0.9285 - val_loss: 0.1135 - val_acc: 0.9672

Epoch 6/20

60000/60000 [=====] - 9s 144us/step - loss: 0.2297 - acc: 0.9379 - val_loss: 0.1090 - val_acc: 0.9682

Epoch 7/20

60000/60000 [=====] - 9s 142us/step - loss: 0.2101 - acc: 0.9415 - val_loss: 0.1017 - val_acc: 0.9728

Epoch 8/20

60000/60000 [=====] - 9s 151us/step - loss: 0.1892 - acc: 0.9485 - val_loss: 0.1001 - val_acc: 0.9720

Epoch 9/20

60000/60000 [=====] - 10s 161us/step - loss: 0.1752 - acc: 0.9520 - val_loss: 0.0922 - val_acc: 0.9747

```

Epoch 10/20
60000/60000 [=====] - 9s 151us/step - loss: 0.1650 - a
cc: 0.9553 - val_loss: 0.0913 - val_acc: 0.9747
Epoch 11/20
60000/60000 [=====] - 9s 148us/step - loss: 0.1473 - a
cc: 0.9586 - val_loss: 0.0832 - val_acc: 0.9761
Epoch 12/20
60000/60000 [=====] - 9s 148us/step - loss: 0.1492 - a
cc: 0.9597 - val_loss: 0.0862 - val_acc: 0.9767
Epoch 13/20
60000/60000 [=====] - 9s 144us/step - loss: 0.1375 - a
cc: 0.9625 - val_loss: 0.0830 - val_acc: 0.9771
Epoch 14/20
60000/60000 [=====] - 9s 142us/step - loss: 0.1322 - a
cc: 0.9637 - val_loss: 0.0860 - val_acc: 0.9757
Epoch 15/20
60000/60000 [=====] - 9s 148us/step - loss: 0.1264 - a
cc: 0.9656 - val_loss: 0.0805 - val_acc: 0.9789
Epoch 16/20
60000/60000 [=====] - 9s 147us/step - loss: 0.1196 - a
cc: 0.9669 - val_loss: 0.0805 - val_acc: 0.9791
Epoch 17/20
60000/60000 [=====] - 9s 146us/step - loss: 0.1127 - a
cc: 0.9698 - val_loss: 0.0819 - val_acc: 0.9781
Epoch 18/20
60000/60000 [=====] - 9s 146us/step - loss: 0.1100 - a
cc: 0.9700 - val_loss: 0.0820 - val_acc: 0.9785
Epoch 19/20
60000/60000 [=====] - 9s 144us/step - loss: 0.1027 - a
cc: 0.9712 - val_loss: 0.0817 - val_acc: 0.9798
Epoch 20/20
60000/60000 [=====] - 8s 142us/step - loss: 0.1001 - a
cc: 0.9721 - val_loss: 0.0781 - val_acc: 0.9794
Model: "sequential_5"

```

Layer (type)	Output Shape	Param #
dense_13 (Dense)	(None, 512)	401920
dropout_9 (Dropout)	(None, 512)	0
dense_14 (Dense)	(None, 128)	65664
dropout_10 (Dropout)	(None, 128)	0
dense_15 (Dense)	(None, 64)	8256
batch_normalization_4 (Batch Normalization)	(None, 64)	256
dropout_11 (Dropout)	(None, 64)	0
dense_16 (Dense)	(None, 10)	650
Total params: 476,746		
Trainable params: 476,618		
Non-trainable params: 128		

Accuracy

```
In [52]: score = model_drop.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

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

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

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

# 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 history.history we will have a list of length equal to number of epochs

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

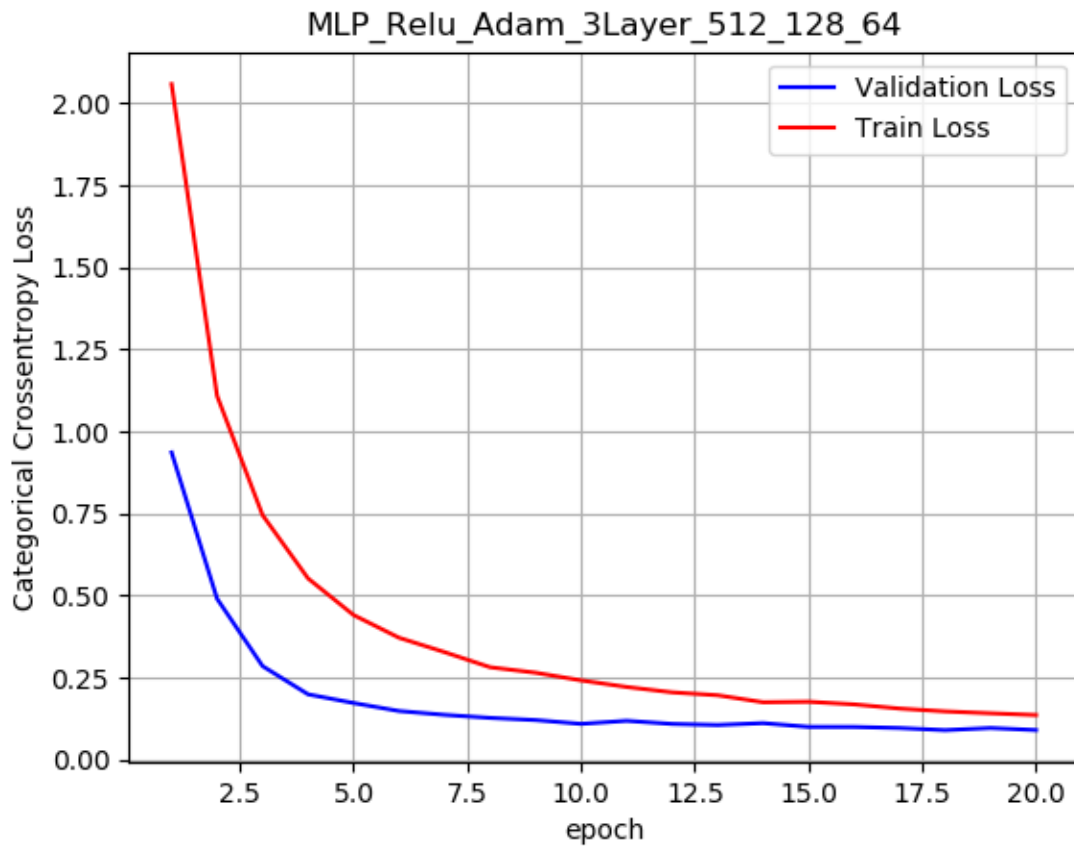
Test score: 0.09080233381008729

Test accuracy: 0.9804

<IPython.core.display.Javascript object>

```
[1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20]
[0.9364621857643127, 0.49075753841400144, 0.2855819786310196, 0.199641513609886
16, 0.17320310388207436, 0.14879324183166026, 0.1371548559397459, 0.12790572729
706765, 0.12123643999770284, 0.10966003392711282, 0.11899310316890478, 0.109499
49248600752, 0.10622592614218593, 0.11184748293552547, 0.10049898426607251, 0.1
0034355153460056, 0.09705943623417988, 0.09053028036076576, 0.0970813074545003
5, 0.09080233482245821]
[2.058573489634196, 1.1087739948590596, 0.7454398405392965, 0.5526444519678751,
0.44117149138450623, 0.37196457761128743, 0.32815683867136636, 0.28217501312891
64, 0.26549448329607644, 0.24212648111979165, 0.22209778400262198, 0.2057082060
8933768, 0.1968686815738678, 0.1755473879337311, 0.1770206745068232, 0.16906047
227780024, 0.15631902202765147, 0.14764749088684717, 0.14192116012970607, 0.136
5976075251897]
```

```
In [5]: %matplotlib notebook
import matplotlib.pyplot as plt
import numpy as np
import time
fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch') ;
ax.set_ylabel('Categorical Crossentropy Loss')
ax.set_title(label="MLP_ReLu_Adam_3Layer_512_128_64")
plt_dynamic(x, vy, ty, ax)
```



Type-III MLP_ReLu_Adam_5Layer_1024_512_128_64_32

```
In [28]: # https://stackoverflow.com/questions/34716454/where-do-i-call-the-batchnormalization-layer
from keras.layers import Dropout

model_drop = Sequential()

model_drop.add(Dense(1024, activation='relu', input_shape=(input_dim,)), kernel_initializer=RandomNormal(mean=0.0, stddev=0.01))
# model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

model_drop.add(Dense(512, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.01)))
# model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

model_drop.add(Dense(128, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.01)))
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

model_drop.add(Dense(64, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.01)))
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

model_drop.add(Dense(32, activation='relu', kernel_initializer=RandomNormal(mean=0.0, stddev=0.01)))
model_drop.add(BatchNormalization())
model_drop.add(Dropout(0.5))

model_drop.add(Dense(output_dim, activation='softmax'))

# print(model_drop.summary())

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

history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epochs, validation_data=(X_val, Y_val))

model_drop.summary()
```

Train on 60000 samples, validate on 10000 samples

Epoch 1/20

60000/60000 [=====] - 25s 415us/step - loss: 2.0586 - acc: 0.3012 - val_loss: 0.9365 - val_acc: 0.7289

Epoch 2/20

60000/60000 [=====] - 23s 391us/step - loss: 1.1088 - acc: 0.6104 - val_loss: 0.4908 - val_acc: 0.8497

Epoch 3/20

60000/60000 [=====] - 23s 384us/step - loss: 0.7454 - acc: 0.7522 - val_loss: 0.2856 - val_acc: 0.9286

Epoch 4/20

60000/60000 [=====] - 23s 385us/step - loss: 0.5526 - acc: 0.8320 - val_loss: 0.1996 - val_acc: 0.9486

Epoch 5/20

60000/60000 [=====] - 24s 394us/step - loss: 0.4412 - acc: 0.8744 - val_loss: 0.1732 - val_acc: 0.9566

Epoch 6/20

60000/60000 [=====] - 23s 380us/step - loss: 0.3720 - acc: 0.8974 - val_loss: 0.1488 - val_acc: 0.9605

```

Epoch 7/20
60000/60000 [=====] - 24s 395us/step - loss: 0.3282 -
acc: 0.9149 - val_loss: 0.1372 - val_acc: 0.9650
Epoch 8/20
60000/60000 [=====] - 23s 378us/step - loss: 0.2822 -
acc: 0.9281 - val_loss: 0.1279 - val_acc: 0.9671
Epoch 9/20
60000/60000 [=====] - 23s 387us/step - loss: 0.2655 -
acc: 0.9334 - val_loss: 0.1212 - val_acc: 0.9700
Epoch 10/20
60000/60000 [=====] - 23s 376us/step - loss: 0.2421 -
acc: 0.9406 - val_loss: 0.1097 - val_acc: 0.9722
Epoch 11/20
60000/60000 [=====] - 23s 387us/step - loss: 0.2221 -
acc: 0.9461 - val_loss: 0.1190 - val_acc: 0.9708
Epoch 12/20
60000/60000 [=====] - 24s 400us/step - loss: 0.2057 -
acc: 0.9511 - val_loss: 0.1095 - val_acc: 0.9740
Epoch 13/20
60000/60000 [=====] - 24s 395us/step - loss: 0.1969 -
acc: 0.9532 - val_loss: 0.1062 - val_acc: 0.9739
Epoch 14/20
60000/60000 [=====] - 24s 393us/step - loss: 0.1755 -
acc: 0.9572 - val_loss: 0.1118 - val_acc: 0.9740
Epoch 15/20
60000/60000 [=====] - 22s 375us/step - loss: 0.1770 -
acc: 0.9590 - val_loss: 0.1005 - val_acc: 0.9766
Epoch 16/20
60000/60000 [=====] - 23s 384us/step - loss: 0.1691 -
acc: 0.9609 - val_loss: 0.1003 - val_acc: 0.9775
Epoch 17/20
60000/60000 [=====] - 24s 403us/step - loss: 0.1563 -
acc: 0.9635 - val_loss: 0.0971 - val_acc: 0.9778
Epoch 18/20
60000/60000 [=====] - 23s 385us/step - loss: 0.1476 -
acc: 0.9653 - val_loss: 0.0905 - val_acc: 0.9785
Epoch 19/20
60000/60000 [=====] - 23s 381us/step - loss: 0.1419 -
acc: 0.9676 - val_loss: 0.0971 - val_acc: 0.9797
Epoch 20/20
60000/60000 [=====] - 23s 390us/step - loss: 0.1366 -
acc: 0.9684 - val_loss: 0.0908 - val_acc: 0.9804
Model: "sequential_6"

```

Layer (type)	Output Shape	Param #
dense_17 (Dense)	(None, 1024)	803840
dropout_12 (Dropout)	(None, 1024)	0
dense_18 (Dense)	(None, 512)	524800
dropout_13 (Dropout)	(None, 512)	0
dense_19 (Dense)	(None, 128)	65664
batch_normalization_5 (Batch Normalization)	(None, 128)	512

dropout_14 (Dropout)	(None, 128)	0
dense_20 (Dense)	(None, 64)	8256
batch_normalization_6 (Batch Normalization)	(None, 64)	256
dropout_15 (Dropout)	(None, 64)	0
dense_21 (Dense)	(None, 32)	2080
batch_normalization_7 (Batch Normalization)	(None, 32)	128
dropout_16 (Dropout)	(None, 32)	0
dense_22 (Dense)	(None, 10)	330
=====		
Total params: 1,405,866		
Trainable params: 1,405,418		
Non-trainable params: 448		

Accuracy


```

In [53]: score = model_drop.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

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

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

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

# 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 history.history we will have a list of length equal to number of epochs

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

```

Test score: 0.09080233381008729

Test accuracy: 0.9804

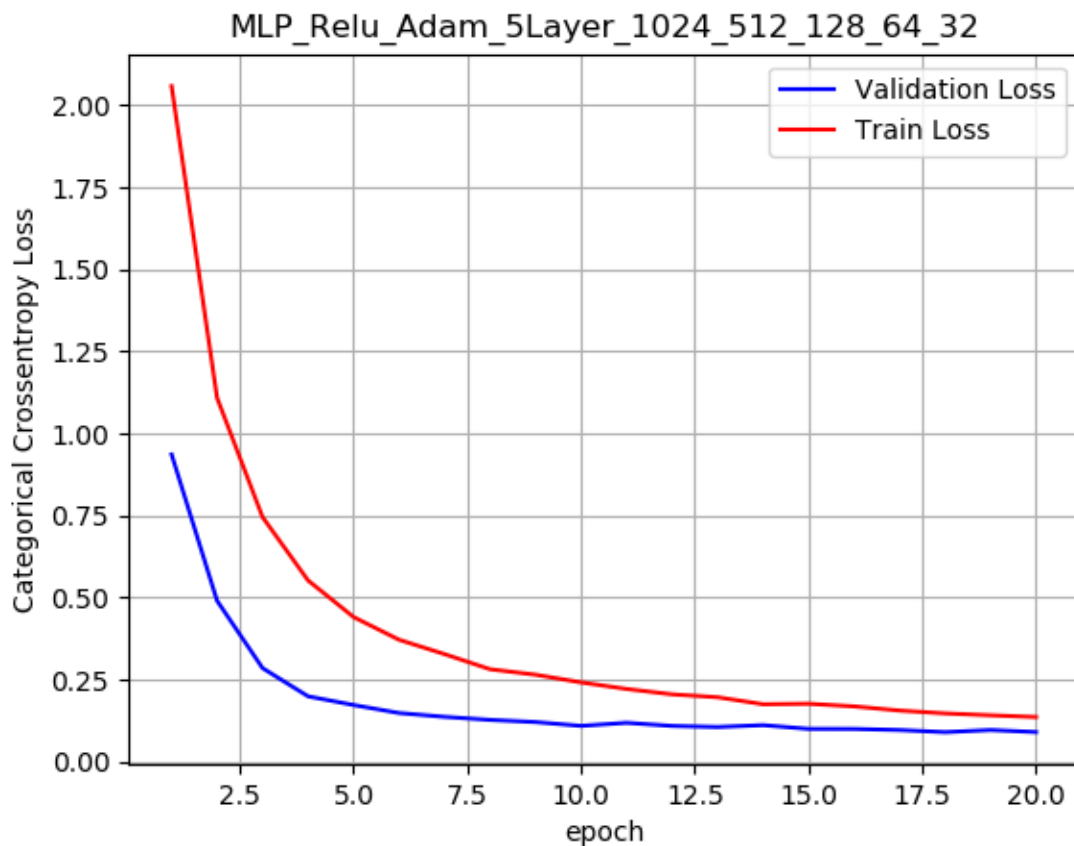
<IPython.core.display.Javascript object>

```

[1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20]
[0.9364621857643127, 0.49075753841400144, 0.2855819786310196, 0.199641513609886
16, 0.17320310388207436, 0.14879324183166026, 0.1371548559397459, 0.12790572729
706765, 0.12123643999770284, 0.10966003392711282, 0.11899310316890478, 0.109499
49248600752, 0.10622592614218593, 0.11184748293552547, 0.10049898426607251, 0.1
0034355153460056, 0.09705943623417988, 0.09053028036076576, 0.0970813074545003
5, 0.09080233482245821]
[2.058573489634196, 1.1087739948590596, 0.7454398405392965, 0.5526444519678751,
0.44117149138450623, 0.37196457761128743, 0.32815683867136636, 0.28217501312891
64, 0.26549448329607644, 0.24212648111979165, 0.22209778400262198, 0.2057082060
8933768, 0.1968686815738678, 0.1755473879337311, 0.1770206745068232, 0.16906047
227780024, 0.15631902202765147, 0.14764749088684717, 0.14192116012970607, 0.136
5976075251897]

```

```
In [7]: %matplotlib notebook
import matplotlib.pyplot as plt
import numpy as np
import time
fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch') ;
ax.set_ylabel('Categorical Crossentropy Loss')
ax.set_title(label="MLP_ReLU_Adam_5Layer_1024_512_128_64_32")
plt_dynamic(x, vy, ty, ax)
```



In []: