MNIST using Keras

June 24, 2019

0.1 Keras -- MLPs on MNIST

```
In [0]: # if you keras is not using tensorflow as backend set "KERAS_BACKEND=tensorflow" use t
        from keras.utils import np_utils
        from keras.datasets import mnist
        import seaborn as sns
        from keras.initializers import RandomNormal

        from keras.models import Sequential
        from keras.layers import Dense, Activation
        from keras.layers.normalization import BatchNormalization
        from keras.layers import Dropout
```

```
In [0]: %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()
            plt.show()
```

```
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
11493376/11490434 [==============================] - 1s 0us/step
```

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

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

```
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   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  49 238 253 253 253 253 253 253 253 253 251  93  82
   82  56  39   0   0   0   0   0   0   0   0   0   0   0   0  18 219 253
  253 253 253 253 198 182 247 241   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0  80 156 107 253 253 205  11   0  43 154
    0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0  14   1 154 253  90   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0   0   0   0 139 253 190   2   0
    0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0  11 190 253  70   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0  35 241
  225 160 108   1   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0  81 240 253 253 119  25   0   0   0
    0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0  45 186 253 253 150  27   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0   0   0   0  16  93 252 253 187
```

```
   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
   0   0   0   0   0   0   0 249 253 249  64   0   0   0   0   0   0   0
   0   0   0   0   0   0   0   0   0   0   0   0   0   0  46 130 183 253
 253 207   2   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
   0   0   0   0  39 148 229 253 253 253 250 182   0   0   0   0   0   0
   0   0   0   0   0   0   0   0   0   0   0   0  24 114 221 253 253 253
 253 201  78   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
   0   0  23  66 213 253 253 253 253 198  81   2   0   0   0   0   0   0
   0   0   0   0   0   0   0   0   0   0  18 171 219 253 253 253 253 195
  80   9   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
  55 172 226 253 253 253 253 244 133  11   0   0   0   0   0   0   0   0
   0   0   0   0   0   0   0   0   0   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 => (X - Xmin)/(Xmax-Xmin) = X/255

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

In [9]:
```
# 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]:
```
# some model parameters

output_dim = 10
input_dim = X_train.shape[1]
```

```
batch_size = 128
nb_epoch = 20
```

```
In [17]: model_relu = Sequential()
         model_relu.add(Dense(512, activation='relu', input_shape=(input_dim,)))
         model_relu.add(Dense(128, activation='relu'))
         model_relu.add(Dense(output_dim, activation='softmax'))

         model_relu.summary()

         model_relu.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accura

         history = model_relu.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, ve
```

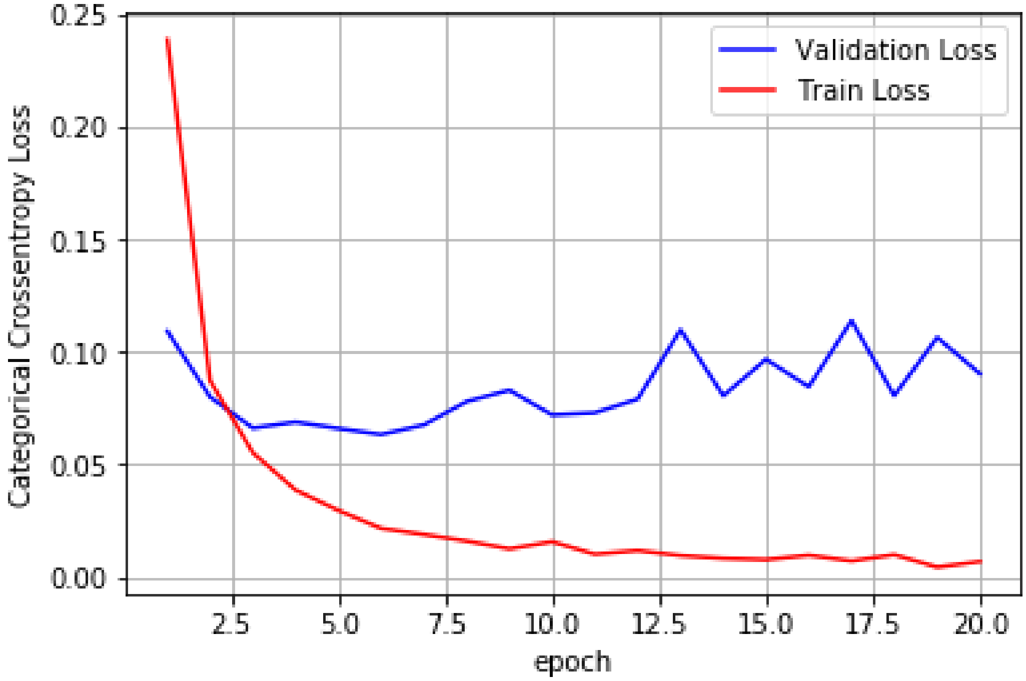
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_4 (Dense)              (None, 512)               401920
_________________________________________________________________
dense_5 (Dense)              (None, 128)               65664
_________________________________________________________________
dense_6 (Dense)              (None, 10)                1290
=================================================================
Total params: 468,874
Trainable params: 468,874
Non-trainable params: 0
_________________________________________________________________
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 7s 121us/step - loss: 0.2420 - acc: 0.9298 - va
Epoch 2/20
60000/60000 [==============================] - 7s 114us/step - loss: 0.0859 - acc: 0.9737 - va
Epoch 3/20
60000/60000 [==============================] - 7s 114us/step - loss: 0.0558 - acc: 0.9829 - va
Epoch 4/20
60000/60000 [==============================] - 7s 116us/step - loss: 0.0372 - acc: 0.9889 - va
Epoch 5/20
60000/60000 [==============================] - 7s 117us/step - loss: 0.0303 - acc: 0.9904 - va
Epoch 6/20
60000/60000 [==============================] - 7s 113us/step - loss: 0.0205 - acc: 0.9931 - va
Epoch 7/20
60000/60000 [==============================] - 7s 113us/step - loss: 0.0182 - acc: 0.9939 - va
Epoch 8/20
60000/60000 [==============================] - 7s 113us/step - loss: 0.0138 - acc: 0.9955 - va
Epoch 9/20
60000/60000 [==============================] - 7s 113us/step - loss: 0.0155 - acc: 0.9948 - va
Epoch 10/20
60000/60000 [==============================] - 7s 114us/step - loss: 0.0148 - acc: 0.9949 - va
```

```
Epoch 11/20
60000/60000 [==============================] - 7s 114us/step - loss: 0.0097 - acc: 0.9969 - va
Epoch 12/20
60000/60000 [==============================] - 7s 114us/step - loss: 0.0095 - acc: 0.9971 - va
Epoch 13/20
60000/60000 [==============================] - 7s 115us/step - loss: 0.0091 - acc: 0.9971 - va
Epoch 14/20
60000/60000 [==============================] - 7s 113us/step - loss: 0.0079 - acc: 0.9977 - va
Epoch 15/20
60000/60000 [==============================] - 7s 114us/step - loss: 0.0128 - acc: 0.9960 - va
Epoch 16/20
60000/60000 [==============================] - 7s 114us/step - loss: 0.0049 - acc: 0.9986 - va
Epoch 17/20
60000/60000 [==============================] - 7s 114us/step - loss: 0.0090 - acc: 0.9971 - va
Epoch 18/20
60000/60000 [==============================] - 7s 112us/step - loss: 0.0075 - acc: 0.9975 - va
Epoch 19/20
60000/60000 [==============================] - 7s 112us/step - loss: 0.0069 - acc: 0.9979 - va
Epoch 20/20
60000/60000 [==============================] - 7s 112us/step - loss: 0.0061 - acc: 0.9982 - va
```

In [16]:
```python
score = model_relu.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

configure_plotly_browser_state()

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 histrory.histrory we will have a list of length equal to number of

vy = history.history['val_loss']
ty = history.history['loss']
```

```
        plt_dynamic(x, vy, ty, ax)
```

```
Test score: 0.09020908048287725
Test accuracy: 0.9836


<IPython.core.display.HTML object>
```



1 Things keep in mind

https://stackoverflow.com/questions/47299624/how-to-understand-loss-acc-val-loss-val-acc-in-keras-model-fitting

Training should be stopped when val_acc stops increasing, otherwise your model will probably overffit. You can use earlystopping callback to stop training.

2 Two Hidden Layers Architecture

```
In [35]: # some model parameters

        output_dim = 10
        input_dim = X_train.shape[1]

        batch_size = 100
```

```
nb_epoch = 20

# 1st Hidden layer
two_layer_model_relu = Sequential()
two_layer_model_relu.add(Dense(400, activation='relu', input_shape=(input_dim,)))
two_layer_model_relu.add(BatchNormalization())
two_layer_model_relu.add(Dropout(0.5))

# 2nd Hidden layer
two_layer_model_relu.add(Dense(100, activation='relu'))
two_layer_model_relu.add(BatchNormalization())
two_layer_model_relu.add(Dropout(0.5))



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

two_layer_model_relu.summary()

two_layer_model_relu.compile(optimizer='adam', loss='categorical_crossentropy', metric

history = two_layer_model_relu.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_
```

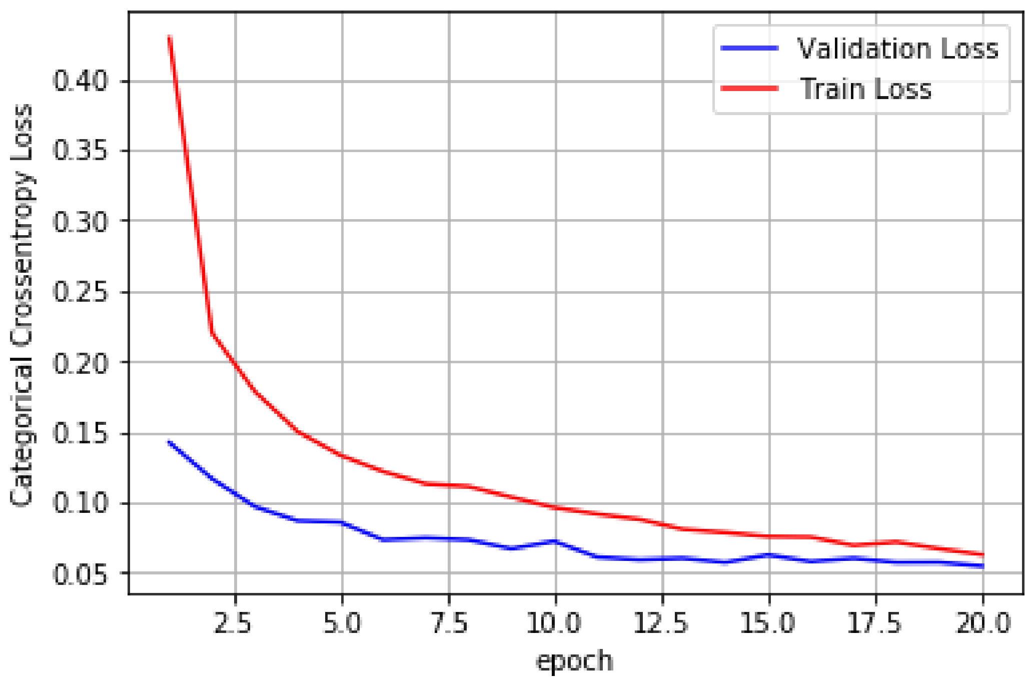
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_32 (Dense)             (None, 400)               314000
_________________________________________________________________
batch_normalization_9 (Batch (None, 400)               1600
_________________________________________________________________
dropout_3 (Dropout)          (None, 400)               0
_________________________________________________________________
dense_33 (Dense)             (None, 100)               40100
_________________________________________________________________
batch_normalization_10 (Batc (None, 100)               400
_________________________________________________________________
dropout_4 (Dropout)          (None, 100)               0
_________________________________________________________________
dense_34 (Dense)             (None, 10)                1010
=================================================================
Total params: 357,110
Trainable params: 356,110
Non-trainable params: 1,000
_________________________________________________________________
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 11s 180us/step - loss: 0.4294 - acc: 0.8712 - va
Epoch 2/20
```

```
60000/60000 [==============================] - 9s 145us/step - loss: 0.2200 - acc: 0.9338 - val
Epoch 3/20
60000/60000 [==============================] - 9s 146us/step - loss: 0.1785 - acc: 0.9468 - val
Epoch 4/20
60000/60000 [==============================] - 9s 146us/step - loss: 0.1502 - acc: 0.9542 - val
Epoch 5/20
60000/60000 [==============================] - 9s 146us/step - loss: 0.1333 - acc: 0.9606 - val
Epoch 6/20
60000/60000 [==============================] - 9s 147us/step - loss: 0.1218 - acc: 0.9638 - val
Epoch 7/20
60000/60000 [==============================] - 9s 152us/step - loss: 0.1130 - acc: 0.9652 - val
Epoch 8/20
60000/60000 [==============================] - 9s 147us/step - loss: 0.1111 - acc: 0.9665 - val
Epoch 9/20
60000/60000 [==============================] - 9s 147us/step - loss: 0.1035 - acc: 0.9685 - val
Epoch 10/20
60000/60000 [==============================] - 9s 148us/step - loss: 0.0962 - acc: 0.9705 - val
Epoch 11/20
60000/60000 [==============================] - 9s 151us/step - loss: 0.0916 - acc: 0.9711 - val
Epoch 12/20
60000/60000 [==============================] - 9s 147us/step - loss: 0.0878 - acc: 0.9729 - val
Epoch 13/20
60000/60000 [==============================] - 9s 147us/step - loss: 0.0808 - acc: 0.9751 - val
Epoch 14/20
60000/60000 [==============================] - 9s 147us/step - loss: 0.0785 - acc: 0.9747 - val
Epoch 15/20
60000/60000 [==============================] - 9s 147us/step - loss: 0.0757 - acc: 0.9773 - val
Epoch 16/20
60000/60000 [==============================] - 9s 147us/step - loss: 0.0752 - acc: 0.9758 - val
Epoch 17/20
60000/60000 [==============================] - 9s 146us/step - loss: 0.0693 - acc: 0.9786 - val
Epoch 18/20
60000/60000 [==============================] - 9s 146us/step - loss: 0.0717 - acc: 0.9778 - val
Epoch 19/20
60000/60000 [==============================] - 9s 146us/step - loss: 0.0669 - acc: 0.9792 - val
Epoch 20/20
60000/60000 [==============================] - 9s 146us/step - loss: 0.0627 - acc: 0.9799 - val
```

In [36]:
```
score = two_layer_model_relu.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 histrory.histrory we will have a list of length equal to number of 

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

```
Test score: 0.054605189490824706
Test accuracy: 0.9833
```



3 Three Hidden Layers Architecture

```
In [39]: # some model parameters
```

```
output_dim = 10
input_dim = X_train.shape[1]

batch_size = 100
nb_epoch = 20

# 1st Hidden layer
three_layer_model_relu = Sequential()
three_layer_model_relu.add(Dense(400, activation='relu', input_shape=(input_dim,)))
three_layer_model_relu.add(BatchNormalization())
three_layer_model_relu.add(Dropout(0.5))

# 2nd Hidden layer
three_layer_model_relu.add(Dense(200, activation='relu'))
three_layer_model_relu.add(BatchNormalization())
three_layer_model_relu.add(Dropout(0.5))

# 3rd Hidden layer
three_layer_model_relu.add(Dense(100, activation='relu'))
three_layer_model_relu.add(BatchNormalization())
three_layer_model_relu.add(Dropout(0.5))


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

three_layer_model_relu.summary()

three_layer_model_relu.compile(optimizer='adam', loss='categorical_crossentropy', met

history = three_layer_model_relu.fit(X_train, Y_train, batch_size=batch_size, epochs=n
```

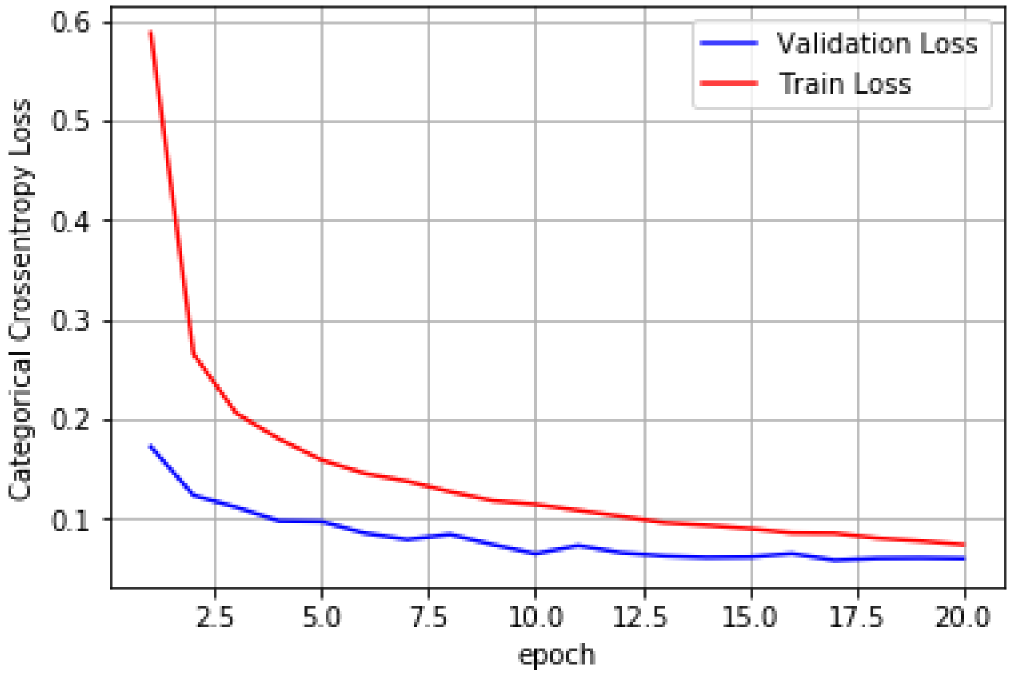
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_40 (Dense)             (None, 400)               314000
_________________________________________________________________
batch_normalization_14 (Batc (None, 400)               1600
_________________________________________________________________
dropout_8 (Dropout)          (None, 400)               0
_________________________________________________________________
dense_41 (Dense)             (None, 200)               80200
_________________________________________________________________
batch_normalization_15 (Batc (None, 200)               800
_________________________________________________________________
dropout_9 (Dropout)          (None, 200)               0
_________________________________________________________________
dense_42 (Dense)             (None, 100)               20100
_________________________________________________________________
```

```
batch_normalization_16 (Batc (None, 100)              400
_________________________________________________________________
dropout_10 (Dropout)         (None, 100)              0
_________________________________________________________________
dense_43 (Dense)             (None, 10)               1010
=================================================================
Total params: 418,110
Trainable params: 416,710
Non-trainable params: 1,400
_________________________________________________________________
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 13s 218us/step - loss: 0.5878 - acc: 0.8226 - va
Epoch 2/20
60000/60000 [==============================] - 10s 169us/step - loss: 0.2655 - acc: 0.9224 - va
Epoch 3/20
60000/60000 [==============================] - 10s 169us/step - loss: 0.2061 - acc: 0.9400 - va
Epoch 4/20
60000/60000 [==============================] - 10s 170us/step - loss: 0.1805 - acc: 0.9487 - va
Epoch 5/20
60000/60000 [==============================] - 10s 170us/step - loss: 0.1593 - acc: 0.9543 - va
Epoch 6/20
60000/60000 [==============================] - 10s 171us/step - loss: 0.1458 - acc: 0.9577 - va
Epoch 7/20
60000/60000 [==============================] - 10s 170us/step - loss: 0.1379 - acc: 0.9598 - va
Epoch 8/20
60000/60000 [==============================] - 10s 170us/step - loss: 0.1274 - acc: 0.9626 - va
Epoch 9/20
60000/60000 [==============================] - 10s 170us/step - loss: 0.1184 - acc: 0.9653 - va
Epoch 10/20
60000/60000 [==============================] - 10s 170us/step - loss: 0.1146 - acc: 0.9657 - va
Epoch 11/20
60000/60000 [==============================] - 10s 169us/step - loss: 0.1087 - acc: 0.9679 - va
Epoch 12/20
60000/60000 [==============================] - 10s 169us/step - loss: 0.1027 - acc: 0.9693 - va
Epoch 13/20
60000/60000 [==============================] - 10s 170us/step - loss: 0.0963 - acc: 0.9721 - va
Epoch 14/20
60000/60000 [==============================] - 10s 168us/step - loss: 0.0936 - acc: 0.9727 - va
Epoch 15/20
60000/60000 [==============================] - 10s 169us/step - loss: 0.0904 - acc: 0.9733 - va
Epoch 16/20
60000/60000 [==============================] - 10s 166us/step - loss: 0.0860 - acc: 0.9741 - va
Epoch 17/20
60000/60000 [==============================] - 10s 165us/step - loss: 0.0856 - acc: 0.9750 - va
Epoch 18/20
60000/60000 [==============================] - 10s 169us/step - loss: 0.0808 - acc: 0.9762 - va
Epoch 19/20
```

```
60000/60000 [==============================] - 10s 170us/step - loss: 0.0779 - acc: 0.9774 - va
Epoch 20/20
60000/60000 [==============================] - 10s 169us/step - loss: 0.0743 - acc: 0.9773 - va
```

```
In [40]: score = three_layer_model_relu.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 histrory.histrory we will have a list of length equal to number of 

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

```
Test score: 0.06033014571936801
Test accuracy: 0.9829
```



4 Five Hidden Layers Architecture

In [43]:
```
# some model parameters

output_dim = 10
input_dim = X_train.shape[1]

batch_size = 100
nb_epoch = 20

# 1st Hidden layer
five_layer_model_relu = Sequential()
five_layer_model_relu.add(Dense(500, activation='relu', input_shape=(input_dim,)))
five_layer_model_relu.add(BatchNormalization())
five_layer_model_relu.add(Dropout(0.5))

# 2nd Hidden layer
five_layer_model_relu.add(Dense(350, activation='relu'))
five_layer_model_relu.add(BatchNormalization())
five_layer_model_relu.add(Dropout(0.5))

# 3rd Hidden layer
five_layer_model_relu.add(Dense(200, activation='relu'))
five_layer_model_relu.add(BatchNormalization())
```

```python
five_layer_model_relu.add(Dropout(0.5))

# 4th Hidden layer
five_layer_model_relu.add(Dense(100, activation='relu'))
five_layer_model_relu.add(BatchNormalization())
five_layer_model_relu.add(Dropout(0.5))

# 5th Hidden layer
five_layer_model_relu.add(Dense(50, activation='relu'))
five_layer_model_relu.add(BatchNormalization())
five_layer_model_relu.add(Dropout(0.5))


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

five_layer_model_relu.summary()

five_layer_model_relu.compile(optimizer='adam', loss='categorical_crossentropy', metri

history = five_layer_model_relu.fit(X_train, Y_train, batch_size=batch_size, epochs=nb
```

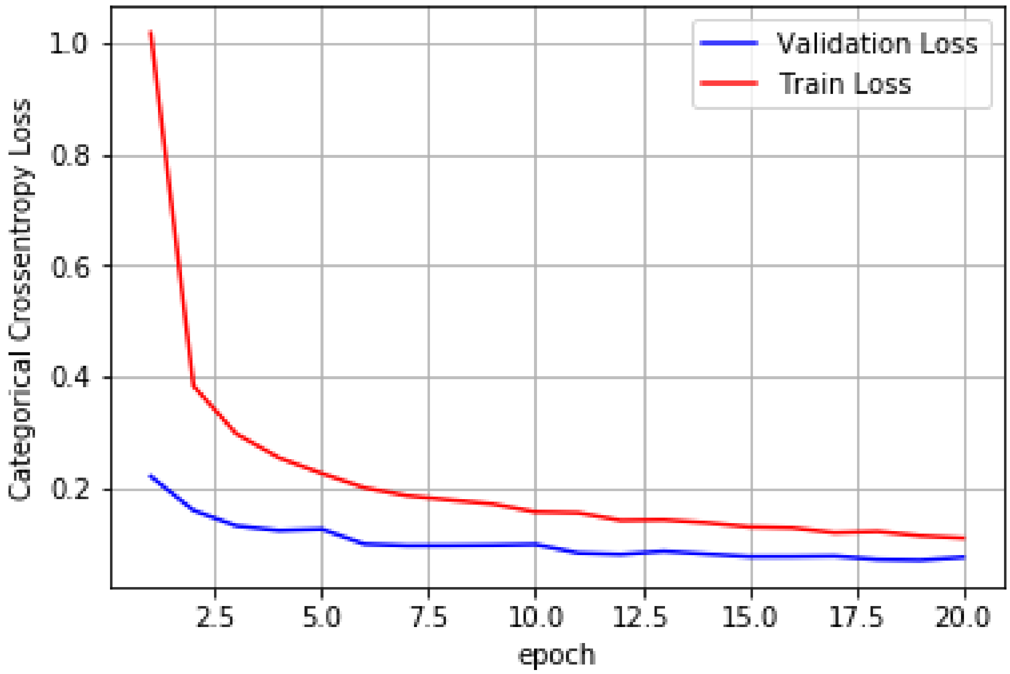
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_50 (Dense)             (None, 500)               392500
_________________________________________________________________
batch_normalization_22 (Batc (None, 500)               2000
_________________________________________________________________
dropout_16 (Dropout)         (None, 500)               0
_________________________________________________________________
dense_51 (Dense)             (None, 350)               175350
_________________________________________________________________
batch_normalization_23 (Batc (None, 350)               1400
_________________________________________________________________
dropout_17 (Dropout)         (None, 350)               0
_________________________________________________________________
dense_52 (Dense)             (None, 200)               70200
_________________________________________________________________
batch_normalization_24 (Batc (None, 200)               800
_________________________________________________________________
dropout_18 (Dropout)         (None, 200)               0
_________________________________________________________________
dense_53 (Dense)             (None, 100)               20100
_________________________________________________________________
batch_normalization_25 (Batc (None, 100)               400
_________________________________________________________________
dropout_19 (Dropout)         (None, 100)               0
_________________________________________________________________
```

```
dense_54 (Dense)             (None, 50)                5050
_________________________________________________________________
batch_normalization_26 (Batc (None, 50)                200
_________________________________________________________________
dropout_20 (Dropout)         (None, 50)                0
_________________________________________________________________
dense_55 (Dense)             (None, 10)                510
=================================================================
Total params: 668,510
Trainable params: 666,110
Non-trainable params: 2,400
_________________________________________________________________
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 20s 338us/step - loss: 1.0178 - acc: 0.6821 - va
Epoch 2/20
60000/60000 [==============================] - 16s 264us/step - loss: 0.3827 - acc: 0.8992 - va
Epoch 3/20
60000/60000 [==============================] - 16s 268us/step - loss: 0.2968 - acc: 0.9235 - va
Epoch 4/20
60000/60000 [==============================] - 16s 269us/step - loss: 0.2536 - acc: 0.9356 - va
Epoch 5/20
60000/60000 [==============================] - 16s 271us/step - loss: 0.2255 - acc: 0.9432 - va
Epoch 6/20
60000/60000 [==============================] - 16s 273us/step - loss: 0.1996 - acc: 0.9498 - va
Epoch 7/20
60000/60000 [==============================] - 16s 267us/step - loss: 0.1852 - acc: 0.9543 - va
Epoch 8/20
60000/60000 [==============================] - 16s 271us/step - loss: 0.1775 - acc: 0.9560 - va
Epoch 9/20
60000/60000 [==============================] - 16s 274us/step - loss: 0.1704 - acc: 0.9583 - va
Epoch 10/20
60000/60000 [==============================] - 16s 271us/step - loss: 0.1560 - acc: 0.9611 - va
Epoch 11/20
60000/60000 [==============================] - 16s 271us/step - loss: 0.1545 - acc: 0.9619 - va
Epoch 12/20
60000/60000 [==============================] - 16s 274us/step - loss: 0.1408 - acc: 0.9652 - va
Epoch 13/20
60000/60000 [==============================] - 17s 275us/step - loss: 0.1418 - acc: 0.9649 - va
Epoch 14/20
60000/60000 [==============================] - 17s 275us/step - loss: 0.1365 - acc: 0.9665 - va
Epoch 15/20
60000/60000 [==============================] - 16s 274us/step - loss: 0.1290 - acc: 0.9686 - va
Epoch 16/20
60000/60000 [==============================] - 16s 272us/step - loss: 0.1274 - acc: 0.9675 - va
Epoch 17/20
60000/60000 [==============================] - 16s 269us/step - loss: 0.1186 - acc: 0.9705 - va
Epoch 18/20
```

```
60000/60000 [==============================] - 16s 267us/step - loss: 0.1209 - acc: 0.9703 - va
Epoch 19/20
60000/60000 [==============================] - 16s 269us/step - loss: 0.1130 - acc: 0.9727 - va
Epoch 20/20
60000/60000 [==============================] - 16s 271us/step - loss: 0.1089 - acc: 0.9729 - va
```

```
In [44]: score = five_layer_model_relu.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 histrory.histrory we will have a list of length equal to number of 

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

```
Test score: 0.07435557465390302
Test accuracy: 0.9829
```



5 Conclusion

```
In [21]: import pandas as pd
         from prettytable import PrettyTable

         bold = '\033[1m'
         end = '\033[0m'


         print(bold+'\t\t\t\t Keras  '+end)
         print('\n')


         print('In Two hidden layers we have used,  neuron architecture is '+bold+str(400)+','
         print('In Three hidden layers we have used,neuron architecture is '+bold+str(400)+','
         print('In Five hidden layers we have used, neuron architecture is '+bold+str(500)+','


         x = PrettyTable()
         x.field_names =  ['Metric','Two Hidden Layer','Three Hidden Layer', 'Five Hidden Laye

         x.add_row(["Train Accuracy ", 0.9799,0.9773,0.9729])
         x.add_row(["Train Loss ", 0.0627,0.0743,0.1089])
```

```
x.add_row(["Validation Accuracy ",0.9833,0.9829,0.9829])
x.add_row(["Validation Loss ", 0.0546,0.0603,0.0744])

x.add_row(["Test Accuracy ",0.9833,0.9829,0.9829])
x.add_row(["Test Loss ", 0.054605,0.06033,0.074355])


print('\n')
print(x)
```

Keras

```
In Two hidden layers we have used,  neuron architecture is 400,100
In Three hidden layers we have used,neuron architecture is 400,200,100
In Five hidden layers we have used, neuron architecture is 500,350,200,100,50
```

Metric	Two Hidden Layer	Three Hidden Layer	Five Hidden Layer
Train Accuracy	0.9799	0.9773	0.9729
Train Loss	0.0627	0.0743	0.1089
Validation Accuracy	0.9833	0.9829	0.9829
Validation Loss	0.0546	0.0603	0.0744
Test Accuracy	0.9833	0.9829	0.9829
Test Loss	0.054605	0.06033	0.074355

In [ ]: