

MLP_on_MNIST (4)

March 15, 2019

0.1 ASSIGNMENT 12

0.1.1 OBJECTIVE: To Build Various MLP architecture for MNIST Dataset

```
In [0]: from keras.utils import np_utils
        from keras.datasets import mnist
        import seaborn as sns
        from keras.initializers import RandomNormal
        from keras.layers import Dropout
        from keras.layers.normalization import BatchNormalization
        from keras.models import Sequential
        from keras.layers import Dense, Activation
        from keras.initializers import he_normal
```

```
In [0]: # loading both training and testing Dataset
        (X_train , y_train) , (X_test , y_test) = mnist.load_data()
```

Downloading data from <https://s3.amazonaws.com/img-datasets/mnist.npz>
11493376/11490434 [=====] - 0s 0us/step

```
In [0]: X_train.shape
```

```
Out[0]: (60000, 28, 28)
```

```
In [0]: print('Number of training points: {}'.format(X_train.shape[0]), ' and each image is {} X {}'.format(X_train.shape[1], X_train.shape[2]))
        print('Number of training points: {}'.format(X_test.shape[0]), ' and each image is {} X {}'.format(X_test.shape[1], X_test.shape[2]))
```

Number of training points: 60000 and each image is 28 X 28 pixel

Number of training points: 10000 and each image is 28 X 28 pixel

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

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

```
<class 'numpy.ndarray'>
```

```
In [0]: # normalizing
X_train = X_train/255
X_test = X_test/255
```

```
In [0]: # 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)           # one hot encoding
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]: 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()
```

0.2 SOFTMAX CLASSIFIER with 2 hidden layers

```
In [0]: # model parameters
output_dim = 10
input_dim = X_train.shape[1]

batch_size = 128
```

```

nb_epoch = 20

# start building a model
model_2_layers = Sequential()

model_2_layers.add(Dense(364, activation='relu', input_shape=(input_dim,), kernel_init.
model_2_layers.add(BatchNormalization()) # batch normalization
model_2_layers.add(Dropout(0.25)) #dropout

model_2_layers.add(Dense(52, activation='relu', kernel_initializer=he_normal(seed = No
model_2_layers.add(BatchNormalization())
model_2_layers.add(Dropout(0.25))

model_2_layers.add(Dense(output_dim, activation='softmax'))

# model Summary
print("Model Summary :- \n",model_2_layers.summary())

# Compiling the model
model_2_layers.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['acc

#training model
history_2_layers = model_2_layers.fit(X_train, Y_train, batch_size=batch_size, epochs=1

```

Layer (type)	Output Shape	Param #
dense_4 (Dense)	(None, 364)	285740
batch_normalization_3 (Batch Normalization)	(None, 364)	1456
dropout_3 (Dropout)	(None, 364)	0
dense_5 (Dense)	(None, 52)	18980
batch_normalization_4 (Batch Normalization)	(None, 52)	208
dropout_4 (Dropout)	(None, 52)	0
dense_6 (Dense)	(None, 10)	530

Total params: 306,914
 Trainable params: 306,082
 Non-trainable params: 832

Model Summary :-

```

None
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [=====] - 6s 100us/step - loss: 0.3387 - acc: 0.9021 - val.
Epoch 2/20
60000/60000 [=====] - 5s 89us/step - loss: 0.1513 - acc: 0.9552 - val.
Epoch 3/20
60000/60000 [=====] - 5s 90us/step - loss: 0.1128 - acc: 0.9653 - val.
Epoch 4/20
60000/60000 [=====] - 5s 89us/step - loss: 0.0917 - acc: 0.9719 - val.
Epoch 5/20
60000/60000 [=====] - 5s 89us/step - loss: 0.0806 - acc: 0.9748 - val.
Epoch 6/20
60000/60000 [=====] - 5s 89us/step - loss: 0.0680 - acc: 0.9784 - val.
Epoch 7/20
60000/60000 [=====] - 5s 90us/step - loss: 0.0629 - acc: 0.9802 - val.
Epoch 8/20
60000/60000 [=====] - 6s 92us/step - loss: 0.0565 - acc: 0.9819 - val.
Epoch 9/20
60000/60000 [=====] - 6s 93us/step - loss: 0.0512 - acc: 0.9839 - val.
Epoch 10/20
60000/60000 [=====] - 5s 91us/step - loss: 0.0485 - acc: 0.9847 - val.
Epoch 11/20
60000/60000 [=====] - 5s 90us/step - loss: 0.0445 - acc: 0.9856 - val.
Epoch 12/20
60000/60000 [=====] - 5s 90us/step - loss: 0.0409 - acc: 0.9871 - val.
Epoch 13/20
60000/60000 [=====] - 5s 91us/step - loss: 0.0410 - acc: 0.9869 - val.
Epoch 14/20
60000/60000 [=====] - 5s 91us/step - loss: 0.0409 - acc: 0.9870 - val.
Epoch 15/20
60000/60000 [=====] - 5s 89us/step - loss: 0.0358 - acc: 0.9880 - val.
Epoch 16/20
60000/60000 [=====] - 5s 91us/step - loss: 0.0337 - acc: 0.9885 - val.
Epoch 17/20
60000/60000 [=====] - 5s 89us/step - loss: 0.0314 - acc: 0.9898 - val.
Epoch 18/20
60000/60000 [=====] - 5s 89us/step - loss: 0.0320 - acc: 0.9896 - val.
Epoch 19/20
60000/60000 [=====] - 5s 89us/step - loss: 0.0311 - acc: 0.9900 - val.
Epoch 20/20
60000/60000 [=====] - 5s 90us/step - loss: 0.0273 - acc: 0.9913 - val.

```

```

In [0]: score = model_2_layers.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')

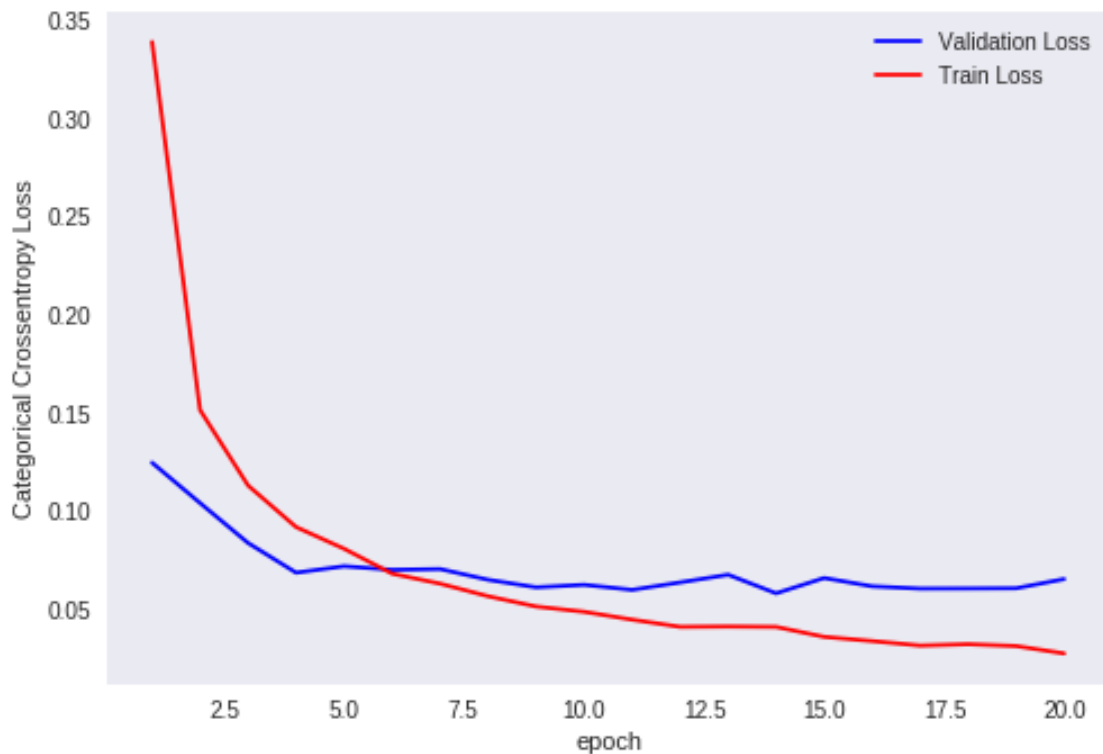
# list of epoch numbers
x = list(range(1,nb_epoch+1))

vy = history_2_layers.history['val_loss'] # validation loss
ty = history_2_layers.history['loss']    # train loss
plt_dynamic(x, vy, ty,ax)

```

Test score: 0.06521892226291966

Test accuracy: 0.9811



3 hidden layers

```

In [0]: # start building a model
model_3_layers = Sequential()

```

```

model_3_layers.add(Dense(400, activation='relu', input_shape=(input_dim,), kernel_init.
model_3_layers.add(BatchNormalization())

```

```

model_3_layers.add(Dropout(0.5))                                #dropout

model_3_layers.add(Dense(300, activation='relu', kernel_initializer=he_normal()))
model_3_layers.add(BatchNormalization())
model_3_layers.add(Dropout(0.5))

model_3_layers.add(Dense(100, activation='relu', kernel_initializer=he_normal()))
model_3_layers.add(BatchNormalization())
model_3_layers.add(Dropout(0.5))

model_3_layers.add(Dense(output_dim, activation='softmax'))

# model Summary
print("Model Summary :- \n",model_3_layers.summary())

# Compiling the model
model_3_layers.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['acc'])

#training model
history_3_layers = model_3_layers.fit(X_train, Y_train, batch_size=batch_size, epochs=10)

score = model_3_layers.evaluate(X_test, Y_test)
print('Test loss:', score[0])
print('Test accuracy:', score[1])

```

Layer (type)	Output Shape	Param #
dense_37 (Dense)	(None, 400)	314000
batch_normalization_21 (Batch Normalization)	(None, 400)	1600
dropout_28 (Dropout)	(None, 400)	0
dense_38 (Dense)	(None, 300)	120300
batch_normalization_22 (Batch Normalization)	(None, 300)	1200
dropout_29 (Dropout)	(None, 300)	0
dense_39 (Dense)	(None, 100)	30100
batch_normalization_23 (Batch Normalization)	(None, 100)	400
dropout_30 (Dropout)	(None, 100)	0
dense_40 (Dense)	(None, 10)	1010

Total params: 468,610
Trainable params: 467,010
Non-trainable params: 1,600

Model Summary :-

None

Train on 60000 samples, validate on 10000 samples

Epoch 1/20

60000/60000 [=====] - 11s 177us/step - loss: 0.6104 - acc: 0.8148 - va

Epoch 2/20

60000/60000 [=====] - 9s 144us/step - loss: 0.2658 - acc: 0.9213 - va

Epoch 3/20

60000/60000 [=====] - 9s 145us/step - loss: 0.2056 - acc: 0.9401 - va

Epoch 4/20

60000/60000 [=====] - 9s 146us/step - loss: 0.1718 - acc: 0.9491 - va

Epoch 5/20

60000/60000 [=====] - 9s 147us/step - loss: 0.1489 - acc: 0.9567 - va

Epoch 6/20

60000/60000 [=====] - 9s 146us/step - loss: 0.1403 - acc: 0.9588 - va

Epoch 7/20

60000/60000 [=====] - 9s 145us/step - loss: 0.1310 - acc: 0.9613 - va

Epoch 8/20

60000/60000 [=====] - 9s 147us/step - loss: 0.1169 - acc: 0.9653 - va

Epoch 9/20

60000/60000 [=====] - 9s 147us/step - loss: 0.1114 - acc: 0.9670 - va

Epoch 10/20

60000/60000 [=====] - 9s 146us/step - loss: 0.1043 - acc: 0.9690 - va

Epoch 11/20

60000/60000 [=====] - 9s 144us/step - loss: 0.0989 - acc: 0.9704 - va

Epoch 12/20

60000/60000 [=====] - 9s 147us/step - loss: 0.0919 - acc: 0.9731 - va

Epoch 13/20

60000/60000 [=====] - 9s 146us/step - loss: 0.0921 - acc: 0.9729 - va

Epoch 14/20

60000/60000 [=====] - 9s 147us/step - loss: 0.0857 - acc: 0.9748 - va

Epoch 15/20

60000/60000 [=====] - 9s 147us/step - loss: 0.0838 - acc: 0.9746 - va

Epoch 16/20

60000/60000 [=====] - 9s 147us/step - loss: 0.0828 - acc: 0.9762 - va

Epoch 17/20

60000/60000 [=====] - 9s 147us/step - loss: 0.0747 - acc: 0.9774 - va

Epoch 18/20

60000/60000 [=====] - 9s 144us/step - loss: 0.0742 - acc: 0.9778 - va

Epoch 19/20

60000/60000 [=====] - 9s 146us/step - loss: 0.0718 - acc: 0.9784 - va

Epoch 20/20

60000/60000 [=====] - 9s 149us/step - loss: 0.0682 - acc: 0.9791 - va

10000/10000 [=====] - 1s 84us/step

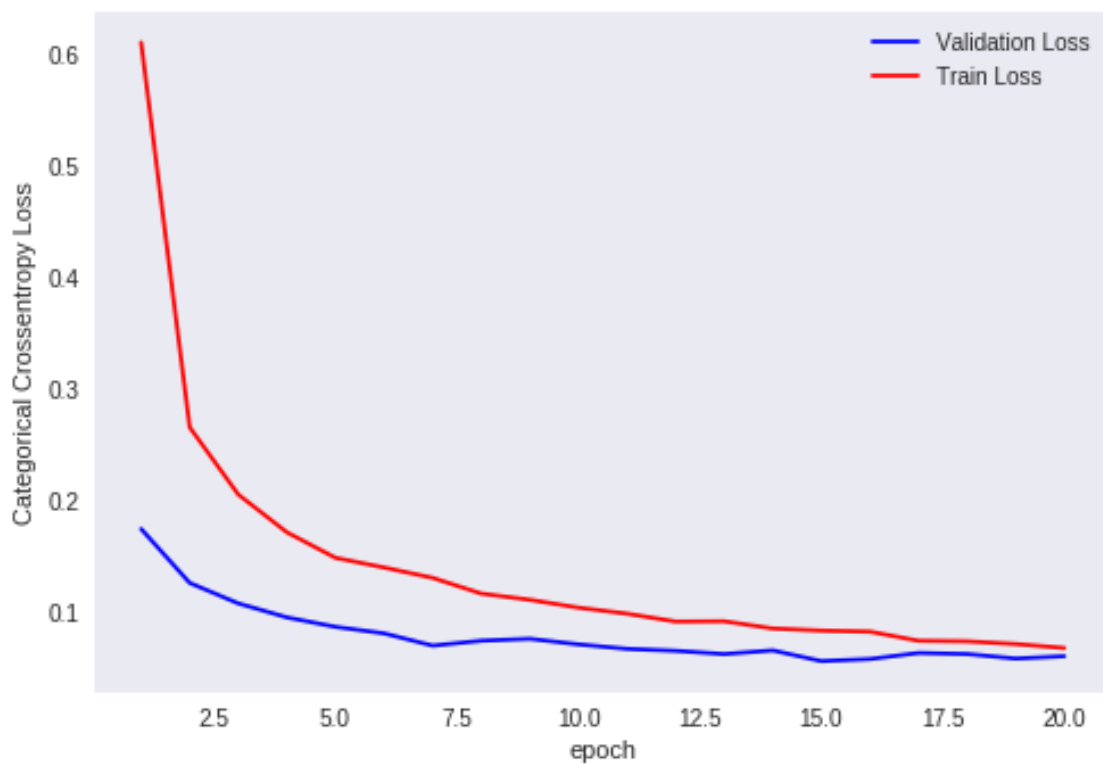
Test loss: 0.060828073866979686

Test accuracy: 0.9821

```
In [0]: fig,ax = plt.subplots(1,1)
        ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')

        x = list(range(1,nb_epoch+1))

        vy = history_3_layers.history['val_loss'] # validation loss
        ty = history_3_layers.history['loss']     # train loss
        plt_dynamic(x, vy, ty,ax)
```



5 Hidden Layers

```
In [0]: from keras.initializers import he_normal
        model_5_layers = Sequential()

        model_5_layers.add(Dense(512, activation='relu', input_shape=(input_dim,), kernel_initializer=he_normal))
        model_5_layers.add(Dropout(0.25))

        model_5_layers.add(Dense(256, activation='relu', kernel_initializer=he_normal))
        model_5_layers.add(Dropout(0.25))
```



```

# batch Normalization
model_5_layers.add(BatchNormalization())

model_5_layers.add(Dense(128 , activation = 'relu' , kernel_initializer = he_normal(see
model_5_layers.add(Dropout(0.25))

model_5_layers.add(Dense(64 , activation = 'relu' , kernel_initializer = he_normal(see
model_5_layers.add(Dropout(0.25))

model_5_layers.add(BatchNormalization())

model_5_layers.add(Dense(32 , activation = 'relu' , kernel_initializer = he_normal(see
model_5_layers.add(Dropout(0.25))

model_5_layers.add(BatchNormalization())

model_5_layers.add(Dense(output_dim, activation='softmax'))

# model Summary
print("Model Summary :- \n",model_5_layers.summary())

# Compiling the model
model_5_layers.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['ac

#training model
history_5_layers = model_5_layers.fit(X_train, Y_train, batch_size=batch_size, epochs=1

score = model_5_layers.evaluate(X_test, Y_test)
print('Test loss:', score[0])
print('Test accuracy:', score[1])

```

Layer (type)	Output Shape	Param #
dense_53 (Dense)	(None, 512)	401920
dropout_41 (Dropout)	(None, 512)	0
dense_54 (Dense)	(None, 256)	131328
dropout_42 (Dropout)	(None, 256)	0
batch_normalization_28 (Batch Normalization)	(None, 256)	1024
dense_55 (Dense)	(None, 128)	32896
dropout_43 (Dropout)	(None, 128)	0

dense_56 (Dense)	(None, 64)	8256
dropout_44 (Dropout)	(None, 64)	0
batch_normalization_29 (Batch Normalization)	(None, 64)	256
dense_57 (Dense)	(None, 32)	2080
dropout_45 (Dropout)	(None, 32)	0
batch_normalization_30 (Batch Normalization)	(None, 32)	128
dense_58 (Dense)	(None, 10)	330

Total params: 578,218
 Trainable params: 577,514
 Non-trainable params: 704

Model Summary :-

None

Train on 60000 samples, validate on 10000 samples

Epoch 1/20

60000/60000 [=====] - 13s 209us/step - loss: 0.7485 - acc: 0.7832 - val_loss: 0.7485 - val_acc: 0.7832

Epoch 2/20

60000/60000 [=====] - 10s 162us/step - loss: 0.2655 - acc: 0.9332 - val_loss: 0.2655 - val_acc: 0.9332

Epoch 3/20

60000/60000 [=====] - 10s 165us/step - loss: 0.1964 - acc: 0.9526 - val_loss: 0.1964 - val_acc: 0.9526

Epoch 4/20

60000/60000 [=====] - 10s 165us/step - loss: 0.1590 - acc: 0.9621 - val_loss: 0.1590 - val_acc: 0.9621

Epoch 5/20

60000/60000 [=====] - 10s 167us/step - loss: 0.1342 - acc: 0.9674 - val_loss: 0.1342 - val_acc: 0.9674

Epoch 6/20

60000/60000 [=====] - 10s 165us/step - loss: 0.1195 - acc: 0.9713 - val_loss: 0.1195 - val_acc: 0.9713

Epoch 7/20

60000/60000 [=====] - 10s 162us/step - loss: 0.1085 - acc: 0.9738 - val_loss: 0.1085 - val_acc: 0.9738

Epoch 8/20

60000/60000 [=====] - 10s 163us/step - loss: 0.0981 - acc: 0.9767 - val_loss: 0.0981 - val_acc: 0.9767

Epoch 9/20

60000/60000 [=====] - 10s 161us/step - loss: 0.0929 - acc: 0.9782 - val_loss: 0.0929 - val_acc: 0.9782

Epoch 10/20

60000/60000 [=====] - 10s 161us/step - loss: 0.0820 - acc: 0.9798 - val_loss: 0.0820 - val_acc: 0.9798

Epoch 11/20

60000/60000 [=====] - 10s 164us/step - loss: 0.0763 - acc: 0.9814 - val_loss: 0.0763 - val_acc: 0.9814

Epoch 12/20

60000/60000 [=====] - 10s 168us/step - loss: 0.0727 - acc: 0.9828 - val_loss: 0.0727 - val_acc: 0.9828

Epoch 13/20

60000/60000 [=====] - 10s 165us/step - loss: 0.0674 - acc: 0.9836 - val_loss: 0.0674 - val_acc: 0.9836

```

Epoch 14/20
60000/60000 [=====] - 10s 165us/step - loss: 0.0638 - acc: 0.9850 - va
Epoch 15/20
60000/60000 [=====] - 10s 167us/step - loss: 0.0587 - acc: 0.9857 - va
Epoch 16/20
60000/60000 [=====] - 10s 166us/step - loss: 0.0559 - acc: 0.9867 - va
Epoch 17/20
60000/60000 [=====] - 10s 164us/step - loss: 0.0557 - acc: 0.9866 - va
Epoch 18/20
60000/60000 [=====] - 10s 163us/step - loss: 0.0530 - acc: 0.9871 - va
Epoch 19/20
60000/60000 [=====] - 10s 164us/step - loss: 0.0508 - acc: 0.9873 - va
Epoch 20/20
60000/60000 [=====] - 10s 165us/step - loss: 0.0478 - acc: 0.9885 - va
10000/10000 [=====] - 1s 89us/step
Test loss: 0.07591400257602218
Test accuracy: 0.9822

```

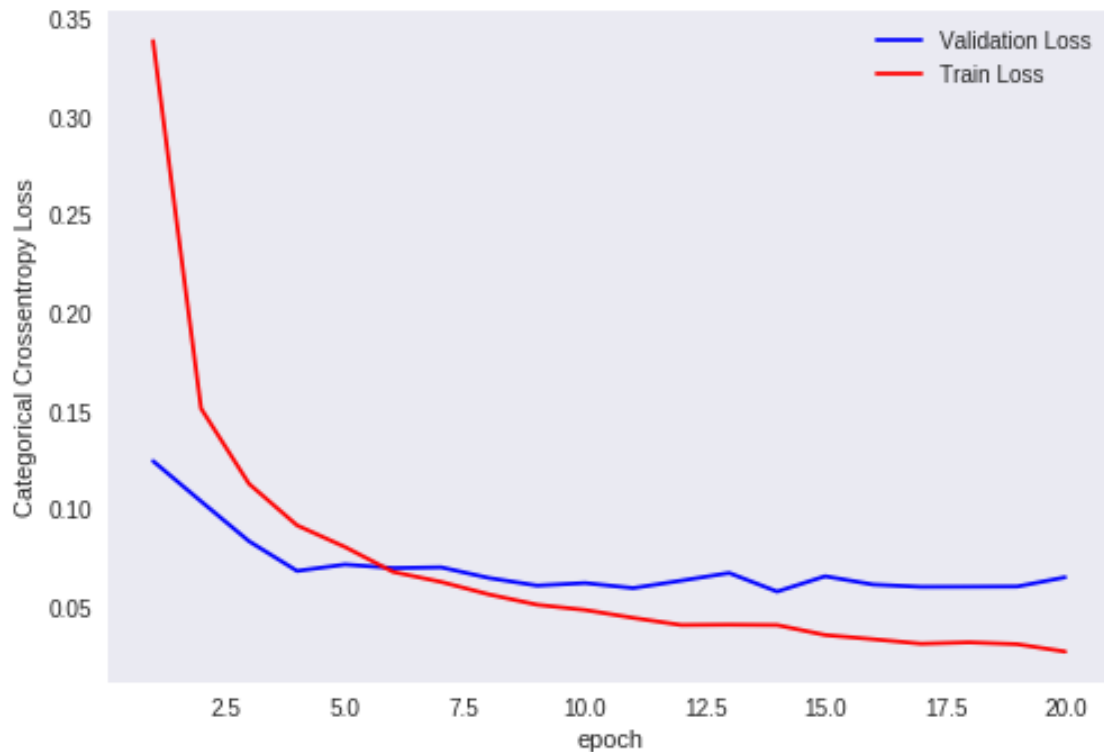
```

In [0]: fig,ax = plt.subplots(1,1)
        ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')

        x = list(range(1,nb_epoch+1))

        vy = history_2_layers.history['val_loss'] # validation loss
        ty = history_2_layers.history['loss']     # train loss
        plt_dynamic(x, vy, ty,ax)

```



OBSERVATION: Deep MLPs are more prone to overfitting hence we can see that validation loss is more compare to train loss as no. of epoch is increasing

```
In [0]: from prettytable import PrettyTable
```

```
In [0]: x = PrettyTable()
```

```
In [0]: x.field_names = ["No. of layers", "Test Loss", "Test Accuracy"]
        x.add_row(['2' , '0.06521', '9811'])
        x.add_row(['3' , '0.06082', '0.9821'])
        x.add_row(['5' , '0.0759', '0.9822'])
```

```
In [0]: print(x)
```

No. of layers	Test Loss	Test Accuracy
2	0.06521	9811
3	0.06082	0.9821
5	0.0759	0.9822

Conclusion

1. Increasing number of hidden layers does not always improve the performance of model
2. Deep MLP are prone to overfitting while shallow MLP are prone to underfitting
3. Overfitting can be avoid using dropout