## Assignment12

#### June 1, 2019

```
In [1]: # 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
Using TensorFlow backend.
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 [0]: # the data, shuffled and split between train and test sets
        (X_train, y_train), (X_test, y_test) = mnist.load_data()
In [4]: print("Number of training examples:", X_train.shape[0], "and each image is of shape (
        print("Number of testing examples: ", X_test.shape[0], "and each image is of shape (%d
Number of training examples: 60000 and each image is of shape (28, 28)
Number of testing 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]: X\_train.shape

Out[6]: (60000, 784)

In [7]: # 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 [8]: # An example data point
 print(X\_train[0])

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66 213 253 253 253 253 198
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```

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  $\# X \Rightarrow (X - Xmin)/(Xmax-Xmin) = X/255$ 

X\_train = X\_train/255
X\_test = X\_test/255

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0.49411765 0.53333333 0.68627451 0.10196078 0.65098039 1.
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                                           1
In [11]: # 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, 0, 1, 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.]
In [0]: from keras.models import Sequential
        from keras.layers import Dense, Activation
        # some model parameters
        output_dim = 10
        input_dim = X_train.shape[1]
        batch_size = 128
```

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## 1 Defining a function for model with dropout as well as batch normalisation

```
In [0]: # https://stackoverflow.com/questions/34716454/where-do-i-call-the-batchnormalization-
from keras.layers import Dropout
    from keras.layers.normalization import BatchNormalization
    from keras import initializers as K

def nn(n_layers,d):
    model = Sequential()
```

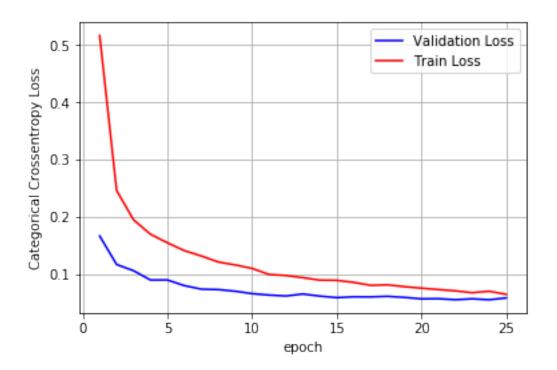
```
model.add(Dense(n_layers[0], activation='relu', input_shape=(input_dim,), kernel_ini
model.add(BatchNormalization())
model.add(Dropout(d[0]))
for i in range(len(n_layers)-1):
 model.add(Dense(n_layers[i+1], activation='relu',kernel_initializer=K.he_normal(see
 model.add(BatchNormalization())
 model.add(Dropout(d[i+1]))
model.add(Dense(output_dim, activation='softmax'))
model.summary()
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy']
history = model.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose
%matplotlib inline
score = model.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))
 #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)
```

#### 1.1 Architecture with 2 hidden layers.

```
In [78]: n_layers = [468,92]
    d = [0.6,0.5]
    nb_epoch = 25
    nn(n_layers,d)
```

```
Output Shape
Layer (type)
                    Param #
______
dense_128 (Dense)
         (None, 468)
                     367380
batch_normalization_85 (Batc (None, 468)
                    1872
dropout_65 (Dropout) (None, 468)
-----
dense 129 (Dense)
          (None, 92)
                    43148
  -----
batch_normalization_86 (Batc (None, 92)
                     368
dropout_66 (Dropout) (None, 92)
_____
dense_130 (Dense) (None, 10)
                     930
______
Total params: 413,698
Trainable params: 412,578
Non-trainable params: 1,120
Train on 60000 samples, validate on 10000 samples
Epoch 1/25
Epoch 2/25
Epoch 3/25
Epoch 4/25
Epoch 5/25
Epoch 6/25
60000/60000 [=============== ] - 4s 66us/step - loss: 0.1410 - acc: 0.9573 - val
Epoch 7/25
Epoch 8/25
60000/60000 [=============== ] - 4s 65us/step - loss: 0.1211 - acc: 0.9641 - val
Epoch 9/25
Epoch 10/25
```

```
Epoch 11/25
Epoch 12/25
Epoch 13/25
Epoch 14/25
Epoch 15/25
Epoch 16/25
60000/60000 [=============== ] - 4s 64us/step - loss: 0.0855 - acc: 0.9730 - val
Epoch 17/25
Epoch 18/25
Epoch 19/25
Epoch 20/25
Epoch 21/25
Epoch 22/25
Epoch 23/25
60000/60000 [============== ] - 4s 64us/step - loss: 0.0674 - acc: 0.9791 - val
Epoch 24/25
Epoch 25/25
Test score: 0.058353246974284415
```

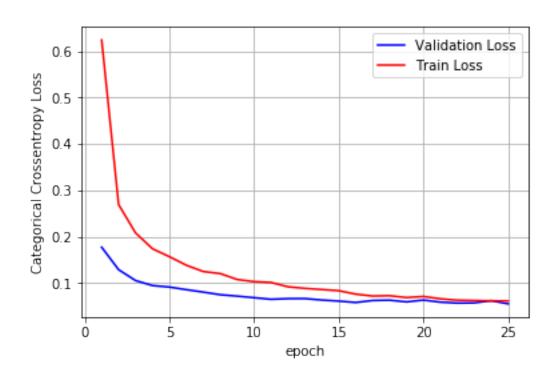


## 1.2 Architecture with 3 hidden layers.

Layer (type)	Output Shape	Param #
dense_131 (Dense)	(None, 512)	401920
batch_normalization_87 (Batch_normalization_87)	(None, 512)	2048
dropout_67 (Dropout)	(None, 512)	0
dense_132 (Dense)	(None, 256)	131328
batch_normalization_88 (Batch_normalization_88)	(None, 256)	1024
dropout_68 (Dropout)	(None, 256)	0
dense_133 (Dense)	(None, 128)	32896
batch_normalization_89 (Batch_	: (None, 128)	512

```
(None, 128)
dropout_69 (Dropout)
dense 134 (Dense)
          (None, 10)
                   1290
______
Total params: 571,018
Trainable params: 569,226
Non-trainable params: 1,792
Train on 60000 samples, validate on 10000 samples
Epoch 1/25
Epoch 2/25
Epoch 3/25
Epoch 4/25
60000/60000 [=============== ] - 5s 76us/step - loss: 0.1737 - acc: 0.9488 - val
Epoch 5/25
Epoch 6/25
Epoch 7/25
Epoch 8/25
60000/60000 [============== ] - 5s 78us/step - loss: 0.1201 - acc: 0.9645 - val
Epoch 9/25
Epoch 10/25
Epoch 11/25
Epoch 12/25
Epoch 13/25
Epoch 14/25
Epoch 15/25
Epoch 16/25
60000/60000 [================ ] - 5s 80us/step - loss: 0.0758 - acc: 0.9770 - val
Epoch 17/25
Epoch 18/25
60000/60000 [=============== ] - 5s 82us/step - loss: 0.0724 - acc: 0.9783 - val
Epoch 19/25
60000/60000 [=============== ] - 5s 81us/step - loss: 0.0684 - acc: 0.9798 - val
```

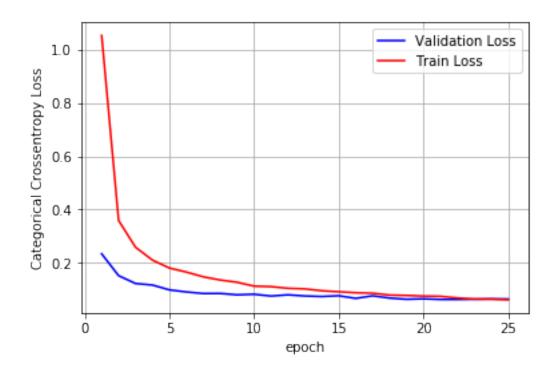
```
Epoch 20/25
Epoch 21/25
60000/60000 [====
                ========] - 5s 79us/step - loss: 0.0657 - acc: 0.9802 - val
Epoch 22/25
60000/60000 [==
                 ========] - 5s 80us/step - loss: 0.0627 - acc: 0.9810 - val
Epoch 23/25
            60000/60000 [=====
Epoch 24/25
60000/60000 [==
                 ========] - 5s 79us/step - loss: 0.0614 - acc: 0.9813 - val
Epoch 25/25
Test score: 0.0548867928153486
```



#### 1.3 Architecture with 4 hidden layers (for experimentation)

```
______
dense_56 (Dense)
              (None, 600)
                            471000
batch_normalization_44 (Batc (None, 600)
                            2400
            (None, 600)
dropout_44 (Dropout)
-----
dense_57 (Dense)
          (None, 460)
                            276460
batch_normalization_45 (Batc (None, 460)
                           1840
dropout_45 (Dropout) (None, 460)
_____
dense 58 (Dense)
             (None, 290)
                           133690
  .....
batch_normalization_46 (Batc (None, 290)
                           1160
dropout_46 (Dropout)
           (None, 290)
   -----
dense 59 (Dense)
           (None, 112)
_____
batch_normalization_47 (Batc (None, 112)
                            448
-----
dropout_47 (Dropout) (None, 112)
-----
dense_60 (Dense)
          (None, 10)
                           1130
______
Total params: 920,720
Trainable params: 917,796
Non-trainable params: 2,924
Train on 60000 samples, validate on 10000 samples
Epoch 1/25
Epoch 2/25
Epoch 3/25
Epoch 4/25
60000/60000 [=============== ] - 5s 90us/step - loss: 0.2100 - acc: 0.9431 - val
Epoch 5/25
60000/60000 [============== ] - 5s 90us/step - loss: 0.1803 - acc: 0.9518 - val
Epoch 6/25
60000/60000 [=============== ] - 5s 91us/step - loss: 0.1652 - acc: 0.9559 - val
Epoch 7/25
Epoch 8/25
60000/60000 [============== ] - 5s 90us/step - loss: 0.1353 - acc: 0.9637 - val
```

```
Epoch 9/25
Epoch 10/25
60000/60000 [=============== ] - 5s 90us/step - loss: 0.1123 - acc: 0.9691 - val
Epoch 11/25
60000/60000 [=============== ] - 5s 90us/step - loss: 0.1104 - acc: 0.9708 - val
Epoch 12/25
Epoch 13/25
60000/60000 [=============== ] - 5s 90us/step - loss: 0.1020 - acc: 0.9728 - val
Epoch 14/25
60000/60000 [============== ] - 5s 90us/step - loss: 0.0949 - acc: 0.9748 - val
Epoch 15/25
Epoch 16/25
Epoch 17/25
60000/60000 [=============== ] - 5s 90us/step - loss: 0.0857 - acc: 0.9771 - val
Epoch 18/25
Epoch 19/25
Epoch 20/25
60000/60000 [=============== ] - 5s 89us/step - loss: 0.0749 - acc: 0.9799 - val
Epoch 21/25
60000/60000 [============== ] - 5s 89us/step - loss: 0.0741 - acc: 0.9804 - val
Epoch 22/25
Epoch 23/25
Epoch 24/25
Epoch 25/25
Test score: 0.06384382131070597
Test accuracy: 0.9847
```

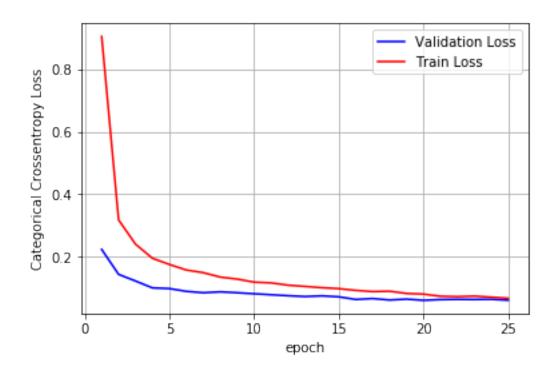


## 1.4 Architecture with 5 hidden layers.

Layer (type)	Output Shape	Param #
dense_72 (Dense)	(None, 650)	510250
batch_normalization_58 (Bat	c (None, 650)	2600
dropout_57 (Dropout)	(None, 650)	0
dense_73 (Dense)	(None, 520)	338520
batch_normalization_59 (Bat	c (None, 520)	2080
dropout_58 (Dropout)	(None, 520)	0
dense_74 (Dense)	(None, 410)	213610
batch_normalization_60 (Bat	c (None, 410)	1640

```
(None, 410)
dropout_59 (Dropout)
         (None, 290)
dense_75 (Dense)
                 119190
batch_normalization_61 (Batc (None, 290)
   _____
dropout_60 (Dropout) (None, 290)
dense_76 (Dense)
        (None, 125)
                 36375
batch_normalization_62 (Batc (None, 125)
                 500
 _____
dropout_61 (Dropout) (None, 125)
-----
dense_77 (Dense) (None, 10)
                 1260
______
Total params: 1,227,185
Trainable params: 1,223,195
Non-trainable params: 3,990
Train on 60000 samples, validate on 10000 samples
Epoch 1/25
Epoch 2/25
Epoch 3/25
Epoch 4/25
Epoch 5/25
Epoch 6/25
Epoch 7/25
Epoch 8/25
Epoch 9/25
Epoch 10/25
60000/60000 [============== ] - 6s 105us/step - loss: 0.1186 - acc: 0.9668 - va
Epoch 11/25
Epoch 12/25
Epoch 13/25
```

```
Epoch 14/25
Epoch 15/25
60000/60000 [=====
                ========] - 6s 107us/step - loss: 0.0978 - acc: 0.9729 - va
Epoch 16/25
60000/60000 [===
                 ========] - 7s 116us/step - loss: 0.0923 - acc: 0.9743 - va
Epoch 17/25
Epoch 18/25
60000/60000 [===
                   =======] - 7s 110us/step - loss: 0.0896 - acc: 0.9744 - va
Epoch 19/25
Epoch 20/25
Epoch 21/25
Epoch 22/25
60000/60000 [============== ] - 6s 107us/step - loss: 0.0722 - acc: 0.9789 - va
Epoch 23/25
60000/60000 [==
                   =======] - 6s 108us/step - loss: 0.0738 - acc: 0.9789 - va
Epoch 24/25
60000/60000 [====
                 ========] - 6s 108us/step - loss: 0.0706 - acc: 0.9795 - va
Epoch 25/25
60000/60000 [=====
                 ========] - 6s 107us/step - loss: 0.0669 - acc: 0.9807 - va
Test score: 0.06073720659725368
```



# 2 Defining a function for model with only batch normalisation and no dropout.

In [0]: # https://stackoverflow.com/questions/34716454/where-do-i-call-the-batchnormalizationdef nn1(n\_layers,bn): model = Sequential() model.add(Dense(n\_layers[0], activation='relu', input\_shape=(input\_dim,), kernel\_ini if(bn==1):model.add(BatchNormalization()) for i in range(len(n\_layers)-1): model.add(Dense(n\_layers[i+1], activation='relu',kernel\_initializer=K.he\_normal( model.add(BatchNormalization()) else: for i in range(len(n\_layers)-1): model.add(Dense(n\_layers[i+1], activation='relu',kernel\_initializer=K.he\_normal() model.add(Dense(output\_dim, activation='softmax')) model.summary() model.compile(optimizer='adam', loss='categorical\_crossentropy', metrics=['accuracy'] history = model.fit(X\_train, Y\_train, batch\_size=batch\_size, epochs=nb\_epoch, verbose %matplotlib inline score = model.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)) #dict\_keys(['val\_loss', 'val\_acc', 'loss', 'acc']) # history = model\_drop.fit(X\_train, Y\_train, batch\_size=batch\_size, epochs=nb\_epoch,

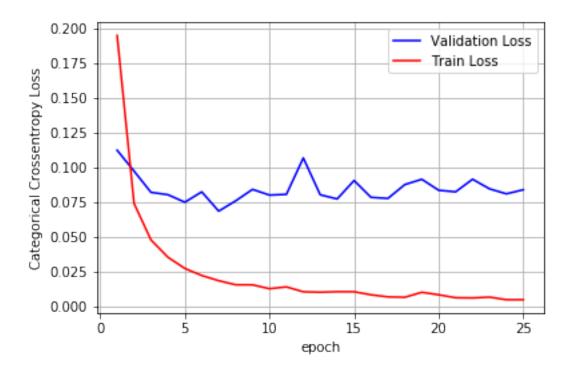
```
# we will get val_loss and val_acc only when you pass the paramter validation_data
# val_loss : validation loss
# val_acc : validation accuracy

# 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)
```

#### 2.0.1 Architecture with 2 hidden layers.

Layer (type)	Output	-	Param #	
dense_102 (Dense)				
batch_normalization_75 (Batc			1872	
dense_103 (Dense)				
batch_normalization_76 (Batc				
dense_104 (Dense)	(None,	10)	930	
Total params: 413,698 Trainable params: 412,578 Non-trainable params: 1,120				
Train on 60000 samples, valid Epoch 1/25 60000/60000 [========		•	 9us/step - 1	oss: 0.1946 – acc: 0.9427 – va
Epoch 2/25 60000/60000 [======= Epoch 3/25	=====	=====] - 4s 62us	s/step - los	s: 0.0741 - acc: 0.9776 - val
Epoch 4/25			_	s: 0.0479 - acc: 0.9853 - val
Epoch 5/25				s: 0.0355 - acc: 0.9889 - val s: 0.0275 - acc: 0.9914 - val

```
Epoch 7/25
Epoch 8/25
Epoch 9/25
60000/60000 [=============== ] - 4s 66us/step - loss: 0.0157 - acc: 0.9948 - val
Epoch 10/25
Epoch 11/25
Epoch 12/25
Epoch 13/25
Epoch 14/25
Epoch 15/25
60000/60000 [=============== ] - 4s 63us/step - loss: 0.0107 - acc: 0.9963 - val
Epoch 16/25
Epoch 17/25
Epoch 18/25
Epoch 19/25
60000/60000 [=============== ] - 4s 62us/step - loss: 0.0103 - acc: 0.9966 - val
Epoch 20/25
Epoch 21/25
Epoch 22/25
Epoch 23/25
Epoch 24/25
Epoch 25/25
Test score: 0.08396656601358045
Test accuracy: 0.9808
```



## 2.1 Architecture with 3 hidden layers.

Layer (type)	Output	Shape	Param #
dense_105 (Dense)	(None,	512)	401920
batch_normalization_77 (Batc	(None,	512)	2048
dense_106 (Dense)	(None,	256)	131328
batch_normalization_78 (Batc	(None,	256)	1024
dense_107 (Dense)	(None,	128)	32896
batch_normalization_79 (Batc	(None,	128)	512
dense_108 (Dense)	(None,	10)	1290 =======

Total params: 571,018

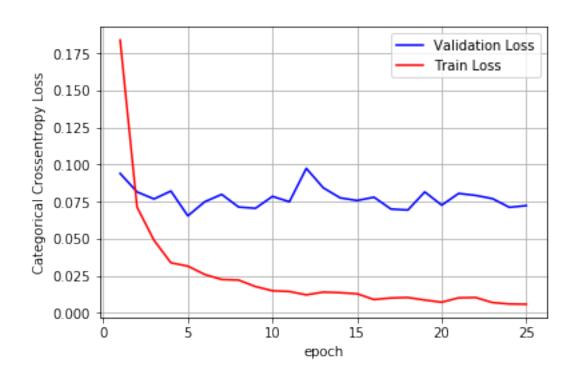
Trainable params: 569,226 Non-trainable params: 1,792

Train on 60000 samples, validate on 10000 samples Epoch 1/25 Epoch 2/25 Epoch 3/25 60000/60000 [=============== ] - 5s 76us/step - loss: 0.0490 - acc: 0.9843 - val Epoch 4/25 60000/60000 [============== ] - 5s 78us/step - loss: 0.0337 - acc: 0.9889 - val Epoch 5/25 Epoch 6/25 Epoch 7/25 60000/60000 [=============== ] - 4s 74us/step - loss: 0.0225 - acc: 0.9926 - val Epoch 8/25 Epoch 9/25 Epoch 10/25 60000/60000 [============== ] - 4s 74us/step - loss: 0.0149 - acc: 0.9950 - val Epoch 11/25 60000/60000 [============== ] - 5s 75us/step - loss: 0.0144 - acc: 0.9955 - val Epoch 12/25 Epoch 13/25 Epoch 14/25 Epoch 15/25 Epoch 16/25 Epoch 17/25 Epoch 18/25 Epoch 19/25 60000/60000 [=============== ] - 5s 76us/step - loss: 0.0086 - acc: 0.9973 - val Epoch 20/25 Epoch 21/25 Epoch 22/25 60000/60000 [=============== ] - 4s 74us/step - loss: 0.0103 - acc: 0.9967 - val

```
Epoch 23/25
Epoch 24/25
60000/60000 [====
                    =======] - 4s 75us/step - loss: 0.0060 - acc: 0.9981 - val
Epoch 25/25
60000/60000 [====
                           =] - 4s 75us/step - loss: 0.0058 - acc: 0.9981 - val
```

Test score: 0.07232702655499207

Test accuracy: 0.9833

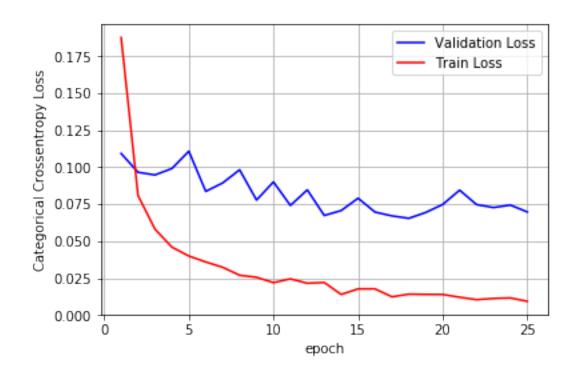


#### 2.2 Architecture with 5 hidden layers.

Layer (type)	Output	Shape	Param #
dense_109 (Dense)	(None,	650)	510250
batch_normalization_80 (Batc	(None,	650)	2600
dense_110 (Dense)	(None,	520)	338520

```
batch_normalization_81 (Batc (None, 520)
                  2080
dense 111 (Dense)
      (None, 410)
                  213610
batch_normalization_82 (Batc (None, 410)
                  1640
_____
dense 112 (Dense)
      (None, 290)
                  119190
batch_normalization_83 (Batc (None, 290)
                  1160
dense_113 (Dense) (None, 125)
                  36375
_____
batch_normalization_84 (Batc (None, 125)
                  500
dense_114 (Dense) (None, 10)
                  1260
______
Total params: 1,227,185
Trainable params: 1,223,195
Non-trainable params: 3,990
Train on 60000 samples, validate on 10000 samples
Epoch 1/25
60000/60000 [============== ] - 15s 242us/step - loss: 0.1877 - acc: 0.9439 - v
Epoch 2/25
Epoch 3/25
Epoch 4/25
Epoch 5/25
Epoch 6/25
Epoch 7/25
Epoch 8/25
Epoch 9/25
Epoch 10/25
Epoch 11/25
Epoch 12/25
Epoch 13/25
```

```
Epoch 14/25
Epoch 15/25
60000/60000 [======
              Epoch 16/25
               60000/60000 [===
Epoch 17/25
Epoch 18/25
60000/60000 [===
                 ========] - 6s 102us/step - loss: 0.0142 - acc: 0.9955 - va
Epoch 19/25
60000/60000 [============== ] - 6s 102us/step - loss: 0.0140 - acc: 0.9953 - va
Epoch 20/25
60000/60000 [============== ] - 6s 103us/step - loss: 0.0139 - acc: 0.9953 - va
Epoch 21/25
Epoch 22/25
Epoch 23/25
60000/60000 [===
                 =======] - 6s 101us/step - loss: 0.0113 - acc: 0.9963 - va
Epoch 24/25
60000/60000 [====
               ========] - 6s 99us/step - loss: 0.0116 - acc: 0.9962 - val
Epoch 25/25
60000/60000 [=======
               ========== ] - 6s 101us/step - loss: 0.0093 - acc: 0.9972 - va
Test score: 0.06976913923782413
```



## 3 Defining a function for model with no dropout and no batch normalisation.

In [0]: # https://stackoverflow.com/questions/34716454/where-do-i-call-the-batchnormalizationdef nn2(n\_layers): model = Sequential() model.add(Dense(n\_layers[0], activation='relu', input\_shape=(input\_dim,), kernel\_ini for i in range(len(n\_layers)-1): model.add(Dense(n\_layers[i+1], activation='relu',kernel\_initializer=K.he\_normal( model.add(Dense(output\_dim, activation='softmax')) model.summary() model.compile(optimizer='adam', loss='categorical\_crossentropy', metrics=['accuracy'] history = model.fit(X\_train, Y\_train, batch\_size=batch\_size, epochs=nb\_epoch, verbose %matplotlib inline score = model.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)) #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

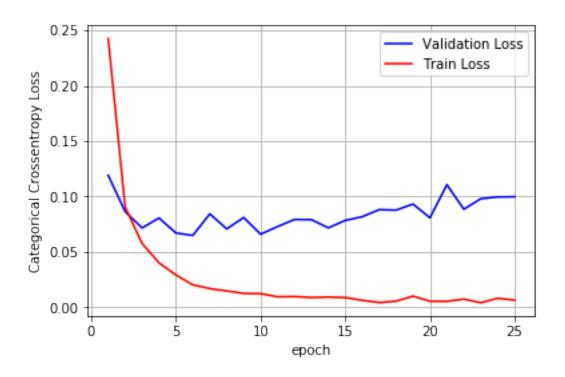
# acc : train accuracy

```
# for each key in history.history we will have a list of length equal to number of
vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
```

### 3.0.1 Architecture with 2 hidden layers.

· · · · · · · · · · · · · · · · · · ·	_	_			· <b>-</b>			
dense_115 (Dense)	(None,	468)		367380	=			
dense_116 (Dense)	(None,			43148	-			
dense_117 (Dense)	(None,			930	. <u> </u>			
Total params: 411,458 Trainable params: 411,458 Non-trainable params: 0					-			
Train on 60000 samples, val Epoch 1/25 60000/60000 [=======			_	)us/step -	 loss: 0.24	125 - ac	c: 0.929	5 - v
Epoch 2/25 60000/60000 [=================================		]	- 3s 42us	s/step - lo	ss: 0.0907	' - acc:	0.9724	- val
60000/60000 [====== Epoch 4/25								
60000/60000 [======= Epoch 5/25 60000/60000 [========				_				
Epoch 6/25 60000/60000 [=======				_				
Epoch 7/25 60000/60000 [=================================		]	- 3s 42us	s/step - lo	ss: 0.0169	) - acc:	0.9944	- val
60000/60000 [======= Epoch 9/25		]	- 3s 42us	s/step - lo	ss: 0.0148	3 - acc:	0.9951	- val
60000/60000 [======== Epoch 10/25				_				
60000/60000 [=================================				_				
Epoch 12/25								

```
Epoch 13/25
Epoch 14/25
60000/60000 [============== ] - 3s 44us/step - loss: 0.0093 - acc: 0.9969 - val
Epoch 15/25
Epoch 16/25
Epoch 17/25
60000/60000 [============== ] - 3s 42us/step - loss: 0.0044 - acc: 0.9986 - val
Epoch 18/25
Epoch 19/25
Epoch 20/25
Epoch 21/25
Epoch 22/25
Epoch 23/25
Epoch 24/25
Epoch 25/25
Test score: 0.09983180044603286
Test accuracy: 0.9807
```



### 3.1 Architecture with 3 hidden layers

Layer (type)	Output Shape	Param #
dense_118 (Dense)	(None, 512)	401920
dense_119 (Dense)	(None, 256)	131328
dense_120 (Dense)	(None, 128)	32896
dense_121 (Dense)	(None, 10)	1290

Total params: 567,434 Trainable params: 567,434 Non-trainable params: 0

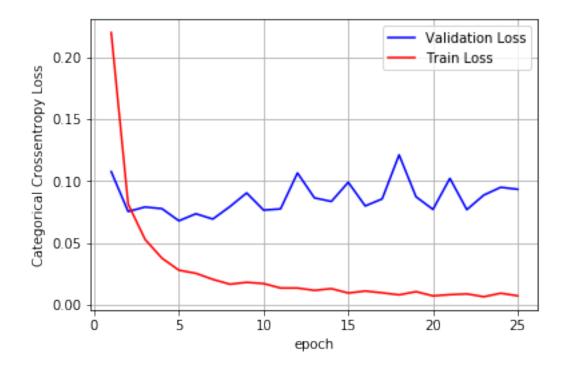
-----

Train on 60000 samples, validate on 10000 samples

Epoch 1/25

Epoch 2/25

```
Epoch 3/25
Epoch 4/25
Epoch 5/25
Epoch 6/25
60000/60000 [=============== ] - 3s 45us/step - loss: 0.0254 - acc: 0.9915 - val
Epoch 7/25
60000/60000 [============== ] - 3s 45us/step - loss: 0.0205 - acc: 0.9932 - val
Epoch 8/25
Epoch 9/25
Epoch 10/25
Epoch 11/25
Epoch 12/25
Epoch 13/25
Epoch 14/25
Epoch 15/25
Epoch 16/25
60000/60000 [=============== ] - 3s 45us/step - loss: 0.0111 - acc: 0.9965 - val
Epoch 17/25
Epoch 18/25
60000/60000 [=============== ] - 3s 45us/step - loss: 0.0080 - acc: 0.9974 - val
Epoch 19/25
Epoch 20/25
60000/60000 [=============== ] - 3s 45us/step - loss: 0.0072 - acc: 0.9980 - val
Epoch 21/25
Epoch 22/25
60000/60000 [=============== ] - 3s 45us/step - loss: 0.0088 - acc: 0.9974 - val
Epoch 23/25
Epoch 24/25
Epoch 25/25
Test score: 0.0932893890325599
```



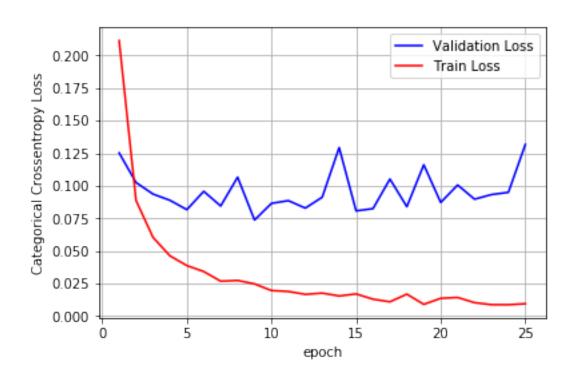
### 3.2 Architecture with 5 hidden layers.

Layer (type)	Output Shape	Param #
dense_122 (Dense)	(None, 650)	510250
dense_123 (Dense)	(None, 520)	338520
dense_124 (Dense)	(None, 410)	213610
dense_125 (Dense)	(None, 290)	119190
dense_126 (Dense)	(None, 125)	36375
dense_127 (Dense)	(None, 10)	1260

Total params: 1,219,205

Trainable params: 1,219,205 Non-trainable params: 0

Train on 60000 samples, validate on 10000 samples Epoch 1/25 60000/60000 [============== ] - 11s 190us/step - loss: 0.2114 - acc: 0.9360 - va Epoch 2/25 Epoch 3/25 60000/60000 [=============== ] - 3s 53us/step - loss: 0.0605 - acc: 0.9813 - val Epoch 4/25 Epoch 5/25 Epoch 6/25 Epoch 7/25 60000/60000 [============== ] - 3s 52us/step - loss: 0.0268 - acc: 0.9914 - val Epoch 8/25 Epoch 9/25 60000/60000 [=============== ] - 3s 52us/step - loss: 0.0248 - acc: 0.9923 - val Epoch 10/25 60000/60000 [============== ] - 3s 52us/step - loss: 0.0196 - acc: 0.9942 - val Epoch 11/25 60000/60000 [============== ] - 3s 52us/step - loss: 0.0189 - acc: 0.9944 - val Epoch 12/25 Epoch 13/25 Epoch 14/25 Epoch 15/25 Epoch 16/25 Epoch 17/25 Epoch 18/25 60000/60000 [=============== ] - 3s 53us/step - loss: 0.0169 - acc: 0.9951 - val Epoch 19/25 Epoch 20/25 Epoch 21/25 Epoch 22/25 60000/60000 [============== ] - 3s 52us/step - loss: 0.0103 - acc: 0.9974 - val



# 4 Defining a function for model with dropout and no batch normalisation.

In [0]: # https://stackoverflow.com/questions/34716454/where-do-i-call-the-batchnormalization-

```
def nn3(n_layers,d):
  model = Sequential()

model.add(Dense(n_layers[0], activation='relu', input_shape=(input_dim,), kernel_inimodel.add(Dropout(d[0]))

for i in range(len(n_layers)-1):
```

model.add(Dense(n\_layers[i+1], activation='relu',kernel\_initializer=K.he\_normal(se

```
model.add(Dropout(d[i+1]))
model.add(Dense(output_dim, activation='softmax'))
model.summary()
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy']
history = model.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose
%matplotlib inline
score = model.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))
#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)
```

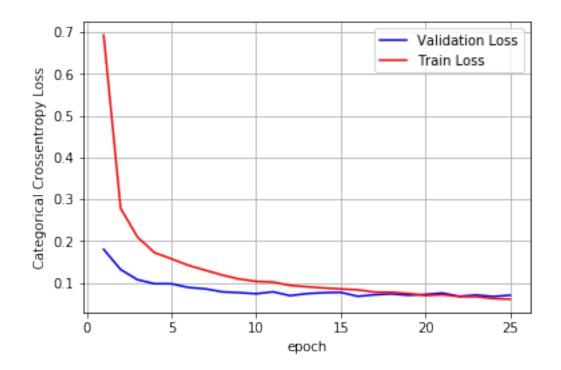
## 5 Architecture with 3 hidden layers.

```
dense_135 (Dense)
             (None, 512)
                         401920
dropout_70 (Dropout) (None, 512)
            (None, 256)
dense 136 (Dense)
-----
dropout_71 (Dropout) (None, 256)
-----
dense_137 (Dense)
            (None, 128)
                         32896
dropout_72 (Dropout) (None, 128)
_____
dense_138 (Dense) (None, 10) 1290
______
Total params: 567,434
Trainable params: 567,434
Non-trainable params: 0
Train on 60000 samples, validate on 10000 samples
Epoch 1/25
Epoch 2/25
60000/60000 [=============== ] - 3s 55us/step - loss: 0.2783 - acc: 0.9225 - val
Epoch 3/25
60000/60000 [============== ] - 3s 53us/step - loss: 0.2091 - acc: 0.9422 - val
Epoch 4/25
Epoch 5/25
Epoch 6/25
Epoch 7/25
Epoch 8/25
Epoch 9/25
Epoch 10/25
60000/60000 [=============== ] - 3s 51us/step - loss: 0.1031 - acc: 0.9710 - val
Epoch 11/25
60000/60000 [=============== ] - 3s 51us/step - loss: 0.1015 - acc: 0.9721 - val
Epoch 12/25
60000/60000 [============== ] - 3s 52us/step - loss: 0.0935 - acc: 0.9738 - val
Epoch 13/25
Epoch 14/25
60000/60000 [============== ] - 3s 52us/step - loss: 0.0874 - acc: 0.9759 - val
```

```
Epoch 15/25
Epoch 16/25
60000/60000 [=====
                  =========] - 3s 52us/step - loss: 0.0830 - acc: 0.9765 - val
Epoch 17/25
                    ========] - 3s 51us/step - loss: 0.0775 - acc: 0.9776 - val
60000/60000 [===
Epoch 18/25
Epoch 19/25
60000/60000 [===
                      ========] - 3s 51us/step - loss: 0.0742 - acc: 0.9796 - val
Epoch 20/25
60000/60000 [=============== ] - 3s 50us/step - loss: 0.0693 - acc: 0.9801 - val
Epoch 21/25
60000/60000 [============== ] - 3s 50us/step - loss: 0.0712 - acc: 0.9803 - val
Epoch 22/25
60000/60000 [============== ] - 3s 51us/step - loss: 0.0669 - acc: 0.9804 - val
Epoch 23/25
60000/60000 [=============== ] - 3s 51us/step - loss: 0.0665 - acc: 0.9805 - val
Epoch 24/25
60000/60000 [===
                    ========] - 3s 51us/step - loss: 0.0622 - acc: 0.9822 - val
Epoch 25/25
60000/60000 [======
```

Test score: 0.07005962141250102

Test accuracy: 0.9826

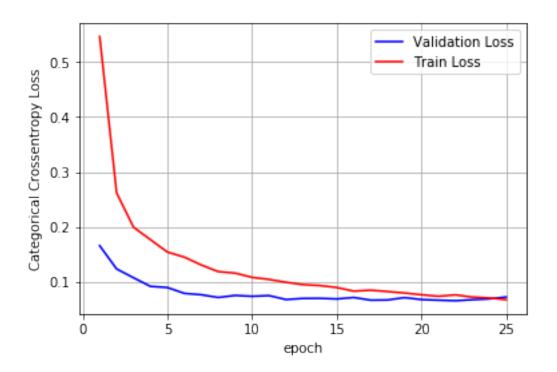


### 6 Architecture with 2 hidden layers.

```
In [82]: n_layers = [468,92]
    d = [0.6,0.5]
    nb_epoch = 25
    nn3(n_layers,d)
```

```
Output Shape Param #
______
dense 139 (Dense)
         (None, 468)
_____
dropout_73 (Dropout) (None, 468)
                 0
_____
dense 140 (Dense)
         (None, 92)
                 43148
-----
dropout_74 (Dropout)
       (None, 92)
-----
dense_141 (Dense) (None, 10)
                 930
______
Total params: 411,458
Trainable params: 411,458
Non-trainable params: 0
Train on 60000 samples, validate on 10000 samples
Epoch 1/25
Epoch 2/25
Epoch 3/25
Epoch 4/25
Epoch 5/25
Epoch 6/25
Epoch 7/25
Epoch 8/25
60000/60000 [============== ] - 3s 48us/step - loss: 0.1191 - acc: 0.9645 - val
Epoch 9/25
60000/60000 [=============== ] - 3s 47us/step - loss: 0.1163 - acc: 0.9656 - val
Epoch 10/25
Epoch 11/25
Epoch 12/25
```

```
Epoch 13/25
60000/60000 [============== ] - 3s 48us/step - loss: 0.0954 - acc: 0.9715 - val
Epoch 14/25
60000/60000 [============== ] - 3s 47us/step - loss: 0.0937 - acc: 0.9730 - val
Epoch 15/25
Epoch 16/25
60000/60000 [=============== ] - 3s 47us/step - loss: 0.0835 - acc: 0.9750 - val
Epoch 17/25
60000/60000 [============== ] - 3s 48us/step - loss: 0.0852 - acc: 0.9744 - val
Epoch 18/25
Epoch 19/25
Epoch 20/25
Epoch 21/25
Epoch 22/25
Epoch 23/25
Epoch 24/25
60000/60000 [=============== ] - 3s 47us/step - loss: 0.0712 - acc: 0.9783 - val
Epoch 25/25
Test score: 0.07291174245599469
```



## 7 Architecture with 5 hidden layers

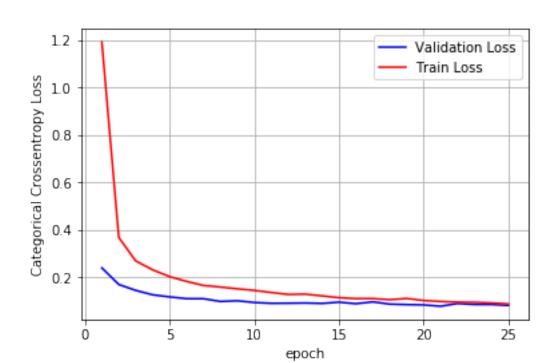
Layer (type)	Output	Shape	Param #
dense_142 (Dense)	(None,	650)	510250
dropout_75 (Dropout)	(None,	650)	0
dense_143 (Dense)	(None,	520)	338520
dropout_76 (Dropout)	(None,	520)	0
dense_144 (Dense)	(None,	410)	213610
dropout_77 (Dropout)	(None,	410)	0
dense_145 (Dense)	(None,	290)	119190

```
._____
dense_146 (Dense)
      (None, 125)
             36375
_____
dropout 79 (Dropout)
     (None, 125)
            0
dense 147 (Dense)
      (None, 10)
            1260
-----
Total params: 1,219,205
Trainable params: 1,219,205
Non-trainable params: 0
Train on 60000 samples, validate on 10000 samples
Epoch 1/25
Epoch 2/25
Epoch 3/25
Epoch 4/25
Epoch 5/25
Epoch 6/25
Epoch 7/25
Epoch 8/25
Epoch 9/25
Epoch 10/25
Epoch 11/25
Epoch 12/25
60000/60000 [=============== ] - 4s 59us/step - loss: 0.1276 - acc: 0.9689 - val
Epoch 13/25
Epoch 14/25
Epoch 15/25
Epoch 16/25
Epoch 17/25
Epoch 18/25
```

dropout\_78 (Dropout)

(None, 290)

```
Epoch 19/25
60000/60000 [============== ] - 4s 60us/step - loss: 0.1106 - acc: 0.9731 - val
Epoch 20/25
                  =======] - 4s 60us/step - loss: 0.1019 - acc: 0.9760 - val
60000/60000 [===
Epoch 21/25
                  =======] - 4s 60us/step - loss: 0.0978 - acc: 0.9759 - val
60000/60000 [===
Epoch 22/25
60000/60000 [==
                  Epoch 23/25
60000/60000 [=============== ] - 4s 60us/step - loss: 0.0943 - acc: 0.9773 - val
Epoch 24/25
Epoch 25/25
Test score: 0.08099026859523369
Test accuracy: 0.9819
```



# 8 Experimenting with conditional batch normalisation and dropout with 3 hidden layers.

In [0]: # https://stackoverflow.com/questions/34716454/where-do-i-call-the-batchnormalizationdef expt():

```
model.add(Dense(584, activation='relu', input_shape=(input_dim,), kernel_initializer
          model.add(BatchNormalization())
          model.add(Dropout(0.5))
          model.add(Dense(320, activation='relu',kernel_initializer=K.he_normal(seed=None)) )
          model.add(BatchNormalization())
          model.add(Dense(125, activation='relu',kernel_initializer=K.he_normal(seed=None)) )
          model.add(Dropout(0.5))
          model.add(Dense(output_dim, activation='softmax'))
          model.summary()
          model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy']
          history = model.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose
          %matplotlib inline
          score = model.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))
           #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)
In [87]: expt()
```

model = Sequential()

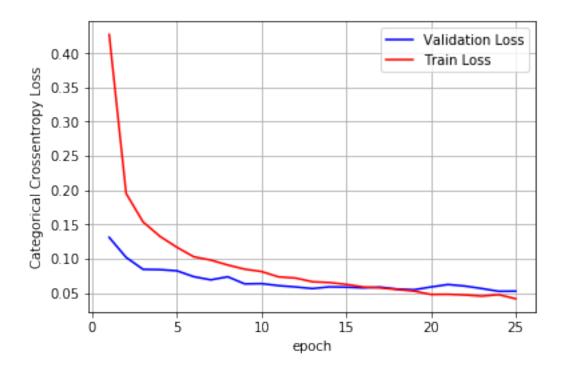
```
______
           (None, 584)
dense_148 (Dense)
                       458440
_____
batch normalization 90 (Batc (None, 584)
                       2336
   -----
dropout_80 (Dropout) (None, 584)
-----
           (None, 320)
dense 149 (Dense)
                       187200
batch_normalization_91 (Batc (None, 320)
                       1280
dense_150 (Dense) (None, 125)
                       40125
  -----
dropout_81 (Dropout) (None, 125)
dense_151 (Dense) (None, 10)
                       1260
______
Total params: 690,641
Trainable params: 688,833
Non-trainable params: 1,808
Train on 60000 samples, validate on 10000 samples
Epoch 1/25
Epoch 2/25
Epoch 3/25
60000/60000 [=============== ] - 4s 73us/step - loss: 0.1537 - acc: 0.9543 - val
Epoch 4/25
60000/60000 [=============== ] - 4s 75us/step - loss: 0.1326 - acc: 0.9605 - val
Epoch 5/25
Epoch 6/25
60000/60000 [=============== ] - 5s 75us/step - loss: 0.1027 - acc: 0.9687 - val
Epoch 7/25
60000/60000 [=============== ] - 5s 76us/step - loss: 0.0979 - acc: 0.9701 - val
Epoch 8/25
Epoch 9/25
Epoch 10/25
Epoch 11/25
Epoch 12/25
Epoch 13/25
```

Output Shape

Param #

Layer (type)

```
60000/60000 [=============== ] - 4s 72us/step - loss: 0.0663 - acc: 0.9793 - val
Epoch 14/25
60000/60000 [=============== ] - 4s 72us/step - loss: 0.0651 - acc: 0.9792 - val
Epoch 15/25
60000/60000 [============== ] - 4s 72us/step - loss: 0.0624 - acc: 0.9805 - val
Epoch 16/25
Epoch 17/25
60000/60000 [=============== ] - 4s 72us/step - loss: 0.0573 - acc: 0.9821 - val
Epoch 18/25
60000/60000 [============== ] - 4s 72us/step - loss: 0.0550 - acc: 0.9823 - val
Epoch 19/25
Epoch 20/25
Epoch 21/25
Epoch 22/25
Epoch 23/25
Epoch 24/25
60000/60000 [=============== ] - 4s 72us/step - loss: 0.0473 - acc: 0.9850 - val
Epoch 25/25
Test score: 0.05252337242660105
```



#### 9 Conclusions

```
In [90]: from prettytable import PrettyTable
       print("======="")
       print(" FOR DROPOUT+BATCH NORMALISATION")
       x = PrettyTable()
       x.field_names = ["No. of hidden layers", "Train Loss", " Val Loss", "Val AUC"]
       x.add_row([2, 0.0645, 0.0584, 0.9828])
       x.add_row([3, 0.0612, 0.0549, 0.9850])
       x.add_row([4, 0.0612, 0.0638, 0.9847])
       x.add row([5, 0.0669, 0.0607, 0.9846])
       print(x)
       print("========="")
       print("========="")
       print(" FOR ONLY BATCH NORMALISATION and NO DROPOUT")
       x = PrettyTable()
       x.field_names = ["No. of hidden layers", "Train Loss", "Val Loss", "Val AUC"]
       x.add_row([2, 0.0050, 0.0840, 0.9808])
       x.add_row([3, 0.0058, 0.0723, 0.9833])
       x.add_row([5, 0.0093, 0.0698, 0.9840])
       print(x)
       print("=====
       print("=
```

```
x = PrettyTable()
     x.field_names = ["No. of hidden layers", "Train Loss", " Val Loss", "Val AUC"]
     x.add_row([2, 0.0065, 0.0998, 0.9807])
     x.add row([3, 0.0072, 0.0933, 0.9814])
     x.add_row([5, 0.0095, 0.1317, 0.9788])
     print(x)
     print("======="")
     print(" FOR DROPOUT ONLY AND NO BATCH NORMALISATION")
     x = PrettyTable()
     x.field_names = ["No. of hidden layers", "Train Loss", "Val Loss", "Val AUC"]
     x.add_row([2, 0.0681, 0.0729, 0.9823])
     x.add_row([3, 0.0605, 0.0701, 0.9826])
     x.add_row([5, 0.0877, 0.0810, 0.9819])
     print(x)
     print("======"")
     print("EXPERIMENTAL DROPOUT-NORMALISATION-DROPOUT")
     x = PrettyTable()
     x.field_names = ["No. of hidden layers", "Train Loss", "Val Loss", "Val AUC"]
     x.add_row([3, 0.0550, 0.0556, 0.9845])
     print(x)
______
FOR DROPOUT+BATCH NORMALISATION
+----+
| No. of hidden layers | Train Loss | Val Loss | Val AUC |
+----+
             | 0.0645 | 0.0584 | 0.9828 |
             | 0.0612 | 0.0549 | 0.985 |
             | 0.0612 | 0.0638 | 0.9847 |
             | 0.0669 | 0.0607 | 0.9846 |
 FOR ONLY BATCH NORMALISATION and NO DROPOUT
+----+
| No. of hidden layers | Train Loss | Val Loss | Val AUC |
+----+
            | 0.005 | 0.084 | 0.9808 |
      3
             | 0.0058 | 0.0723 | 0.9833 |
             | 0.0093 | 0.0698 | 0.984 |
______
```

print(" FOR NO DROPOUT AND NO BATCH NORMALISATION")

#### FOR NO DROPOUT AND NO BATCH NORMALISATION

+	<b></b>	<b>L</b>	L
No. of hidden layers	Train Loss	Val Loss	Val AUC
	0.0065		
3	0.0072	0.0933	0.9814
	0.0095		
	- +		
FOR DROPOUT ONLY AND NO			+
No. of hidden layers	Train Loss	Val Loss	Val AUC
	0.0681		
3	0.0605	0.0701	0.9826
	0.0877		
+	+	· =========	++ ===============================
EXPERIMENTAL _ DROPOUT-N	NORMALISATION-		·
No. of hidden layers	Train Loss	Val Loss	Val AUC
	0.055	0.0556	0.9845

#### 9.0.1 Conclusions

- 1) Observing all the pretty tables, we conclude that ( Dropout+Batch Normalisation) > only Dropout > only batch normalisation > no dropout or normalisation
- 2) As can be observed form the graphs , overfitting occurs, wherever there is no dropout or batch normalisation.
- 3) The best model was found from the experimental model.(Considering upto epoch 18.) It was done as: For this, drop out was applied on first hidden layer. Then, batch normalisation on second hidden layer. Then again, dropout on third hidden layer. This way,instead of applying both of them on all layers, time and cost of computing was saved. The result was also good. The diff between train loss and val loss was 0.0006 at epoch 18(Least of all models). Other models took till epoch near to 25 to converge.
- 4) We can infer that dropout and batch normalisation helps a lot in deep learning models especially in avoiding overfitting.