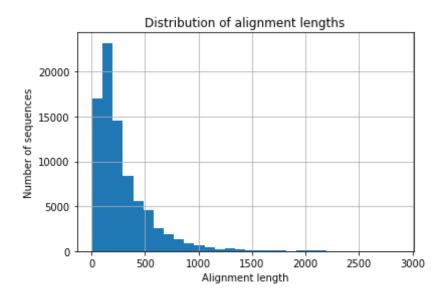
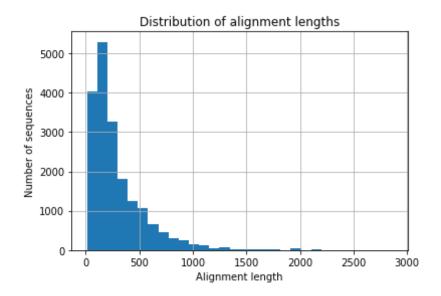
```
In [0]: import pandas as pd
        import numpy as np
In [2]: !pip install -U -g PyDrive
        from pydrive.auth import GoogleAuth
        from pydrive.drive import GoogleDrive
        from google.colab import auth
        from oauth2client.client import GoogleCredentials
        # Authenticate and create the PyDrive client.
        auth.authenticate user()
        gauth = GoogleAuth()
        gauth.credentials = GoogleCredentials.get_application_default()
        drive = GoogleDrive(gauth)
                                                993kB 45.6MB/s
          Building wheel for PyDrive (setup.py) ... done
In [0]: link = 'https://drive.google.com/open?id=1wLPB72yau1pfH8uMp4Mx1Wo0sopd7
        Y2r' # The shareable link
In [0]: fluff, id = link.split('=')
In [0]: downloaded = drive.CreateFile({'id':id})
        downloaded.GetContentFile('traindataframeuploadfinalforsubmission.csv')
        traindataframe= pd.read csv('traindataframeuploadfinalforsubmission.cs
        v',nrows=130000)
In [0]: link = 'https://drive.google.com/open?id=1-e0aY1FCfhTZ0y7uAlRN3j6MOMdvX
        YeS' # The shareable link
In [0]: fluff, id = link.split('=')
```

```
In [0]: downloaded = drive.CreateFile({'id':id})
         downloaded.GetContentFile('testdataframeuploadfinalforsubmission.csv')
         testdataframe= pd.read csv('testdataframeuploadfinalforsubmission.csv',
         nrows=20072)
In [11]: print(testdataframe.shape)
         (20000, 6)
In [0]: link = 'https://drive.google.com/open?id=1S8YirWWFIgpxNLugiTjiIAAtyuIeR
         A7r' # The shareable link
In [0]: fluff, id = link.split('=')
In [0]: downloaded = drive.CreateFile({'id':id})
         downloaded.GetContentFile('cvdataframeuploadfinalforsubmission.csv')
         cvdataframe= pd.read csv('cvdataframeuploadfinalforsubmission.csv')
In [0]: fd=pd.DataFrame()
         import matplotlib.pyplot as plt
         fd['alignment length'] = traindataframe.aligned sequence.str.len()
         fd.alignment length.hist(bins=30)
         plt.title('Distribution of alignment lengths')
         plt.xlabel('Alignment length')
         plt.ylabel('Number of sequences')
Out[0]: <matplotlib.text.Text at 0x2519beec5f8>
```



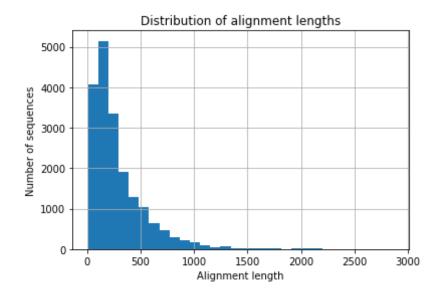
```
In [0]: fd1=pd.DataFrame()
   fd1['alignment_length'] = testdataframe.aligned_sequence.str.len()
   fd1.alignment_length.hist(bins=30)
   plt.title('Distribution of alignment lengths')
   plt.xlabel('Alignment length')
   plt.ylabel('Number of sequences')
```

Out[0]: <matplotlib.text.Text at 0x25191d42c50>



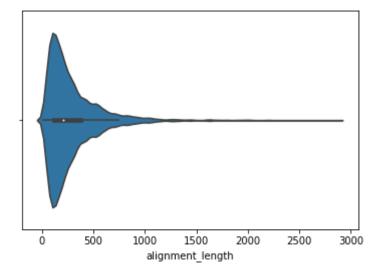
```
In [0]: fd2=pd.DataFrame()
    fd2['alignment_length'] = cvdataframe.aligned_sequence.str.len()
    fd2.alignment_length.hist(bins=30)
    plt.title('Distribution of alignment lengths')
    plt.xlabel('Alignment length')
    plt.ylabel('Number of sequences')
```

Out[0]: <matplotlib.text.Text at 0x251a52e2f98>



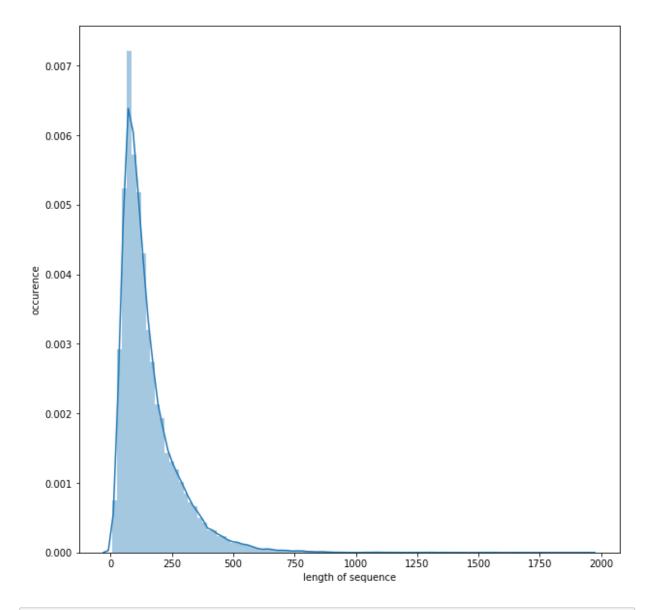
```
In [0]: import seaborn as sns
sns.violinplot(fd['alignment_length'])
```

Out[0]: <matplotlib.axes._subplots.AxesSubplot at 0x251926946d8>



```
In [0]: from sklearn.feature_extraction.text import CountVectorizer
        vect1=CountVectorizer()
        out1=vect1.fit transform(totaldataframe['family id'])
        features1=vect1.get_feature_names()
        counts1=out1.sum(axis=0)
        print('number of unique families are',len(features1))
        number of unique families are 13562
In [0]: from sklearn.feature extraction.text import CountVectorizer
        vect=CountVectorizer()
        out=vect.fit transform(totaldataframe['family accession'])
In [0]: traincount=traindataframe1['family accession'].value counts()
        plt.plot(traincount.values)
Out[0]: [<matplotlib.lines.Line2D at 0x25199e09978>]
         300
         250
         200
         150
         100
          50
           0
                   2000
                        4000
                              6000
                                         10000
                                               12000
                                    8000
In [0]: lengthofsequence=traindataframe['sequence'].apply(lambda x: len(x))
In [0]: print(lengthofsequence.values)
        [169 86 46 ... 65 90 57]
```

```
In [0]: import seaborn as sns
  plt.figure(figsize=(10,10))
    sns.distplot(lengthofsequence.values,hist=True,bins=100)
    plt.xlabel('length of sequence')
    plt.ylabel('occurence')
Out[0]: <matplotlib.text.Text at 0x251a2af2c88>
```



```
In [0]: import string
  def string_vectorizer(strng, alphabet=string.ascii_lowercase):
     vector = [[0 if char != letter else 1 for char in alphabet]
```

```
for letter in strng]
            vector1=np.array(vector)
            shapeout=vector1.shape[0]
            diff=200-shapeout
            reshapearray=np.zeros((diff,26),dtype=int)
            lenarray=len(strng)
            finalarray=np.vstack((vector, reshapearray, newarray))
            return finalarray
In [0]: trainarray1=[]
        for sen in traindataframe['sequence']:
           trainarray1.append(string vectorizer(sen.lower()))
In [0]: testarray1=[]
        for sen in testdataframe['sequence']:
            testarray1.append(string vectorizer(sen.lower()))
In [0]: cvarray1=[]
        for sen in cvdataframe['sequence']:
            cvarray1.append(string vectorizer(sen.lower()))
In [0]: trainarray1=np.array(trainarray1).reshape(130000,200,26)
In [0]: testarray1=np.array(testarray1).reshape(20000,200,26)
        cvarray1=np.array(cvarray1).reshape(20000,200,26)
In [0]: totaldataframe=pd.concat([traindataframe, testdataframe],axis=0)
In [0]: from sklearn.feature extraction.text import CountVectorizer
```

```
vect=CountVectorizer()
         out=vect.fit transform(totaldataframe['family accession'])
         features=vect.get feature names()
         counts=out.sum(axis=0)
In [0]: from keras.models import Sequential
         from keras.layers import Flatten, Activation, Dense, Dropout
         from keras.utils import np utils
In [0]: from sklearn.preprocessing import LabelEncoder
         label1=LabelEncoder()
         label1.fit(totaldataframe['family accession'])
         trainy=label1.transform(traindataframe['family accession'])
         testy=label1.transform(testdataframe['family accession'])
         cvy=label1.transform(cvdataframe['family accession'])
In [0]: # this function is used draw Binary Crossentropy Loss VS No. of epochs
          plot
         def plt dynamic(x, vy, ty):
           plt.figure(figsize=(10,5))
           plt.plot(x, vy, 'b', label="Validation Loss")
           plt.plot(x, ty, 'r', label="Train Loss")
           plt.xlabel('Epochs')
           plt.ylabel('Binary Crossentropy Loss')
           plt.title('\nBinary Crossentropy Loss VS Epochs')
           plt.legend()
           plt.grid()
           plt.show()
In [24]: import keras as keras
         import tensorflow as tf
         from keras.models import Sequential
         from keras.layers import Dense,Dropout,Flatten,BatchNormalization
         from keras.layers import Conv1D, MaxPooling1D
         model=Sequential()
         model.add(Conv1D(100,kernel size=(21),activation='relu',input_shape=(20)
         0,26)))
         model.add(MaxPooling1D(pool size=2))
```

```
model.add(Dropout(0.5))
model.add(BatchNormalization())
model.add(Conv1D(250,26,activation='relu'))
model.add(MaxPooling1D(pool size=4))
model.add(Dropout(0.6))
model.add(BatchNormalization())
model.add(Flatten())
model.add(Dense(11180.activation='softmax'))
model.compile(loss=keras.losses.sparse categorical crossentropy,optimiz
er='adam',metrics=['accuracy'])
history=model.fit(trainarray1,trainy,epochs=70,validation data=[testarr
ay1, testy], batch size=128)
W0618 18:56:06.568818 139743238666112 nn ops.py:4224] Large dropout rat
e: 0.6 (>0.5). In TensorFlow 2.x, dropout() uses dropout rate instead o
f keep prob. Please ensure that this is intended.
W0618 18:56:06.841839 139743238666112 deprecation.py:3231 From /usr/loc
al/lib/python3.6/dist-packages/tensorflow/python/ops/math grad.py:1250:
add dispatch support.<locals>.wrapper (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
Train on 130000 samples, validate on 20000 samples
Epoch 1/70
s: 5.7690 - acc: 0.2431 - val loss: 4.1239 - val acc: 0.3526
Epoch 2/70
s: 2.1282 - acc: 0.6275 - val loss: 3.1806 - val acc: 0.4644
Epoch 3/70
s: 1.0520 - acc: 0.7813 - val loss: 1.9398 - val acc: 0.6472
Epoch 4/70
s: 0.6432 - acc: 0.8529 - val loss: 1.4035 - val acc: 0.7410
Epoch 5/70
s: 0.4576 - acc: 0.8898 - val loss: 1.2556 - val acc: 0.7703
Epoch 6/70
120000/120000 [__
                                        112c 060uc/c+on 1cc
```

```
130000/130000 [=============== ] - 1135 809US/Step - LOS
s: 0.3547 - acc: 0.9109 - val loss: 0.8780 - val acc: 0.8448
Epoch 7/70
s: 0.2904 - acc: 0.9263 - val loss: 0.8866 - val acc: 0.8447
Epoch 8/70
s: 0.2575 - acc: 0.9338 - val_loss: 0.8659 - val_acc: 0.8517
Epoch 9/70
s: 0.2224 - acc: 0.9425 - val loss: 0.7825 - val acc: 0.8648
Epoch 10/70
s: 0.2035 - acc: 0.9464 - val loss: 0.7975 - val acc: 0.8652
Epoch 11/70
s: 0.1886 - acc: 0.9511 - val loss: 0.7368 - val acc: 0.8810
Epoch 12/70
s: 0.1727 - acc: 0.9547 - val loss: 0.7894 - val acc: 0.8694
Epoch 13/70
s: 0.1663 - acc: 0.9571 - val loss: 0.7784 - val acc: 0.8756
Epoch 14/70
s: 0.1540 - acc: 0.9604 - val loss: 0.7448 - val acc: 0.8809
Epoch 15/70
s: 0.1495 - acc: 0.9616 - val loss: 0.7589 - val acc: 0.8790
Epoch 16/70
s: 0.1390 - acc: 0.9637 - val loss: 0.7803 - val acc: 0.8771
Epoch 17/70
s: 0.1355 - acc: 0.9648 - val loss: 0.7963 - val acc: 0.8770
Epoch 18/70
s: 0.1337 - acc: 0.9662 - val loss: 0.7456 - val acc: 0.8835
Epoch 19/70
```

```
s: 0.1237 - acc: 0.9687 - val loss: 0.8482 - val acc: 0.8694
Epoch 20/70
s: 0.1180 - acc: 0.9699 - val loss: 0.8330 - val acc: 0.8685
Epoch 21/70
s: 0.1180 - acc: 0.9696 - val_loss: 0.8984 - val_acc: 0.8591
Epoch 22/70
s: 0.1113 - acc: 0.9716 - val loss: 0.8394 - val acc: 0.8720
Epoch 23/70
s: 0.1076 - acc: 0.9731 - val loss: 0.8682 - val acc: 0.8674
Epoch 24/70
s: 0.1038 - acc: 0.9737 - val loss: 0.7545 - val acc: 0.8857
Epoch 25/70
s: 0.1023 - acc: 0.9740 - val loss: 0.7933 - val acc: 0.8801
Epoch 26/70
s: 0.0984 - acc: 0.9751 - val loss: 0.8213 - val acc: 0.8781
Epoch 27/70
s: 0.0970 - acc: 0.9758 - val loss: 0.8161 - val acc: 0.8785
Epoch 28/70
s: 0.0951 - acc: 0.9758 - val loss: 0.8145 - val acc: 0.8796
Epoch 29/70
s: 0.0908 - acc: 0.9766 - val loss: 0.8507 - val acc: 0.8701
Epoch 30/70
s: 0.0907 - acc: 0.9771 - val loss: 0.8163 - val acc: 0.8780
Epoch 31/70
s: 0.0864 - acc: 0.9782 - val loss: 0.8379 - val acc: 0.8741
Epoch 32/70
```

```
s: 0.0850 - acc: 0.9784 - val_loss: 0.7650 - val_acc: 0.8848
Epoch 33/70
s: 0.0808 - acc: 0.9793 - val loss: 0.8455 - val acc: 0.8759
Epoch 34/70
s: 0.0789 - acc: 0.9799 - val_loss: 0.7777 - val_acc: 0.8846
Epoch 35/70
s: 0.0778 - acc: 0.9804 - val loss: 0.8512 - val acc: 0.8707
Epoch 36/70
s: 0.0760 - acc: 0.9809 - val_loss: 0.7819 - val acc: 0.8850
Epoch 37/70
s: 0.0748 - acc: 0.9811 - val loss: 0.8929 - val acc: 0.8682
Epoch 38/70
s: 0.0755 - acc: 0.9810 - val loss: 0.8348 - val acc: 0.8783
Epoch 39/70
s: 0.0723 - acc: 0.9816 - val loss: 0.8440 - val acc: 0.8764
Epoch 40/70
s: 0.0711 - acc: 0.9820 - val loss: 0.8757 - val acc: 0.8721
Epoch 41/70
s: 0.0699 - acc: 0.9827 - val loss: 0.8580 - val acc: 0.8770
Epoch 42/70
s: 0.0693 - acc: 0.9823 - val loss: 0.8636 - val acc: 0.8764
Epoch 43/70
s: 0.0662 - acc: 0.9835 - val loss: 0.8575 - val acc: 0.8759
Epoch 44/70
s: 0.0658 - acc: 0.9833 - val loss: 0.7781 - val acc: 0.8868
Epoch 45/70
```

```
s: 0.0644 - acc: 0.9833 - val loss: 0.8697 - val acc: 0.8740
Epoch 46/70
s: 0.0621 - acc: 0.9840 - val loss: 0.8078 - val acc: 0.8831
Epoch 47/70
s: 0.0592 - acc: 0.9848 - val_loss: 0.7940 - val_acc: 0.8854
Epoch 48/70
s: 0.0597 - acc: 0.9847 - val loss: 0.7380 - val acc: 0.8949
Epoch 49/70
s: 0.0624 - acc: 0.9842 - val_loss: 0.8336 - val acc: 0.8794
Epoch 50/70
s: 0.0579 - acc: 0.9853 - val loss: 0.7954 - val acc: 0.8854
Epoch 51/70
s: 0.0574 - acc: 0.9853 - val loss: 0.8689 - val acc: 0.8755
Epoch 52/70
s: 0.0566 - acc: 0.9857 - val loss: 0.8988 - val acc: 0.8711
Epoch 53/70
s: 0.0555 - acc: 0.9857 - val loss: 0.8346 - val acc: 0.8800
Epoch 54/70
s: 0.0530 - acc: 0.9862 - val loss: 1.0208 - val acc: 0.8511
Epoch 55/70
s: 0.0526 - acc: 0.9864 - val loss: 0.7981 - val acc: 0.8838
Epoch 56/70
s: 0.0525 - acc: 0.9864 - val loss: 0.8352 - val acc: 0.8786
Epoch 57/70
s: 0.0524 - acc: 0.9867 - val loss: 0.8263 - val acc: 0.8814
Epoch 58/70
```

```
s: 0.0519 - acc: 0.9862 - val loss: 0.9964 - val acc: 0.8572
Epoch 59/70
s: 0.0525 - acc: 0.9867 - val loss: 0.7538 - val acc: 0.8932
Epoch 60/70
s: 0.0501 - acc: 0.9872 - val_loss: 0.8136 - val_acc: 0.8853
Epoch 61/70
s: 0.0504 - acc: 0.9870 - val loss: 0.8633 - val acc: 0.8766
Epoch 62/70
s: 0.0490 - acc: 0.9877 - val loss: 0.7601 - val acc: 0.8905
Epoch 63/70
s: 0.0474 - acc: 0.9877 - val loss: 0.8829 - val acc: 0.8750
Epoch 64/70
s: 0.0489 - acc: 0.9876 - val loss: 0.7767 - val acc: 0.8882
Epoch 65/70
s: 0.0490 - acc: 0.9874 - val loss: 0.8346 - val acc: 0.8799
Epoch 66/70
s: 0.0464 - acc: 0.9882 - val loss: 0.8580 - val acc: 0.8760
Epoch 67/70
s: 0.0457 - acc: 0.9885 - val loss: 0.8592 - val acc: 0.8777
Epoch 68/70
s: 0.0467 - acc: 0.9882 - val loss: 0.8854 - val acc: 0.8767
Epoch 69/70
s: 0.0470 - acc: 0.9879 - val loss: 0.7671 - val acc: 0.8929
Epoch 70/70
s: 0.0448 - acc: 0.9887 - val loss: 0.7847 - val acc: 0.8873
```

```
In [23]: import keras as keras
       import tensorflow as tf
       from keras.models import Sequential
       from keras.layers import Dense,Dropout,Flatten,BatchNormalization
       from keras.layers import Conv1D, MaxPooling1D
       from keras.layers import LSTM
       model=Sequential()
       model.add(Conv1D(300,kernel size=(21),activation='relu',input shape=(20)
       0,26)))
       model.add(MaxPooling1D(pool size=2))
       model.add(Dropout(0.4))
       model.add(BatchNormalization())
       model.add(Conv1D(250,26,activation='relu'))
       model.add(MaxPooling1D(pool size=4))
       model.add(Dropout(0.6))
       model.add(BatchNormalization())
       model.add(LSTM(300,dropout=0.4,return sequences=True))
       model.add(Flatten())
       model.add(Dense(11180,activation='softmax'))
       model.compile(loss=keras.losses.sparse categorical crossentropy,optimiz
       er='adam', metrics=['accuracy'])
       history=model.fit(trainarray1,trainy,epochs=70,validation data=[testarr
       ay1, testy], batch size=128)
       W0619 05:54:02.029180 139960010635136 nn ops.py:4224] Large dropout rat
       e: 0.6 (>0.5). In TensorFlow 2.x, dropout() uses dropout rate instead o
       f keep prob. Please ensure that this is intended.
       Train on 130000 samples, validate on 20000 samples
       Epoch 1/70
       s: 4.9852 - acc: 0.2799 - val loss: 1.9962 - val acc: 0.6245
       Epoch 2/70
       s: 1.6706 - acc: 0.6640 - val loss: 1.0969 - val acc: 0.7780
       Epoch 3/70
       s: 0.7416 - acc: 0.8196 - val loss: 0.9559 - val acc: 0.8147
       Epoch 4/70
```

```
$: ๒.4ววช - acc: ๒.ชช๒๐ - val เบรร: ๒.५๖๖๖ - val acc: ๒.ช๖๒๖
Epoch 5/70
130000/130000 [=============== ] - 114s 879us/step - los
s: 0.3307 - acc: 0.9079 - val loss: 0.8951 - val acc: 0.8394
Epoch 6/70
s: 0.2645 - acc: 0.9257 - val loss: 0.8944 - val acc: 0.8469
Epoch 7/70
s: 0.2243 - acc: 0.9352 - val loss: 0.8788 - val acc: 0.8512
Epoch 8/70
s: 0.1914 - acc: 0.9447 - val loss: 0.8882 - val acc: 0.8536
Epoch 9/70
s: 0.1705 - acc: 0.9497 - val loss: 0.8974 - val acc: 0.8546
Epoch 10/70
s: 0.1536 - acc: 0.9552 - val loss: 0.8856 - val acc: 0.8614
Epoch 11/70
s: 0.1377 - acc: 0.9590 - val loss: 0.8921 - val acc: 0.8627
Epoch 12/70
s: 0.1257 - acc: 0.9629 - val loss: 0.9089 - val acc: 0.8601
Epoch 13/70
s: 0.1162 - acc: 0.9655 - val loss: 0.9008 - val acc: 0.8655
Epoch 14/70
s: 0.1102 - acc: 0.9676 - val loss: 0.9064 - val acc: 0.8652
Epoch 15/70
s: 0.1007 - acc: 0.9701 - val loss: 0.9010 - val acc: 0.8659
Epoch 16/70
s: 0.0981 - acc: 0.9709 - val loss: 0.9005 - val acc: 0.8691
Epoch 17/70
a. 0 0000
      200. 0 0727   val locc. 0 0120   val 200. 0 0660
```

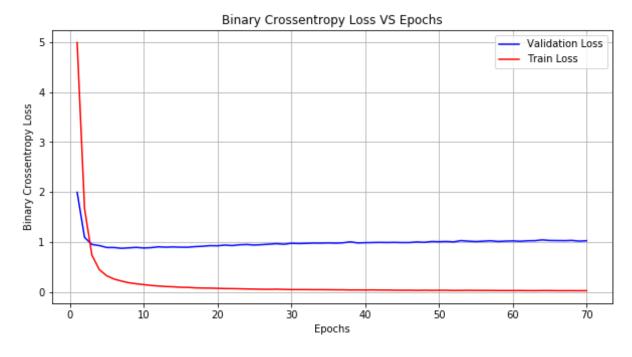
```
5: ช.ชชช - acc: ช.ช/ว/ - val toss: ช.ช129 - val acc: ช.ช00ช
Epoch 18/70
s: 0.0852 - acc: 0.9748 - val loss: 0.9198 - val acc: 0.8697
Epoch 19/70
s: 0.0837 - acc: 0.9756 - val loss: 0.9320 - val acc: 0.8696
Epoch 20/70
s: 0.0798 - acc: 0.9764 - val loss: 0.9294 - val acc: 0.8719
Epoch 21/70
s: 0.0751 - acc: 0.9778 - val loss: 0.9433 - val acc: 0.8716
Epoch 22/70
s: 0.0736 - acc: 0.9779 - val loss: 0.9338 - val acc: 0.8727
Epoch 23/70
s: 0.0705 - acc: 0.9793 - val loss: 0.9497 - val acc: 0.8718
Epoch 24/70
s: 0.0670 - acc: 0.9799 - val loss: 0.9546 - val acc: 0.8720
Epoch 25/70
s: 0.0644 - acc: 0.9809 - val loss: 0.9439 - val acc: 0.8721
Epoch 26/70
s: 0.0614 - acc: 0.9820 - val loss: 0.9518 - val acc: 0.8734
Epoch 27/70
s: 0.0600 - acc: 0.9821 - val loss: 0.9610 - val acc: 0.8721
Epoch 28/70
s: 0.0630 - acc: 0.9817 - val loss: 0.9718 - val acc: 0.8720
Epoch 29/70
s: 0.0584 - acc: 0.9830 - val loss: 0.9599 - val acc: 0.8741
Epoch 30/70
a. 0 0E40
```

```
S: U.U340 - acc: U.9041 - Val lOSS: U.9/93 - Val acc: U.0/23
Epoch 31/70
130000/130000 [============== ] - 115s 882us/step - los
s: 0.0545 - acc: 0.9844 - val loss: 0.9744 - val acc: 0.8738
Epoch 32/70
s: 0.0547 - acc: 0.9840 - val loss: 0.9775 - val acc: 0.8730
Epoch 33/70
s: 0.0526 - acc: 0.9846 - val loss: 0.9838 - val acc: 0.8720
Epoch 34/70
s: 0.0527 - acc: 0.9847 - val loss: 0.9818 - val acc: 0.8726
Epoch 35/70
s: 0.0518 - acc: 0.9850 - val loss: 0.9866 - val acc: 0.8749
Epoch 36/70
s: 0.0501 - acc: 0.9855 - val loss: 0.9820 - val acc: 0.8739
Epoch 37/70
s: 0.0499 - acc: 0.9856 - val loss: 0.9883 - val acc: 0.8750
Epoch 38/70
s: 0.0464 - acc: 0.9864 - val loss: 1.0078 - val acc: 0.8733
Epoch 39/70
s: 0.0475 - acc: 0.9864 - val loss: 0.9859 - val acc: 0.8753
Epoch 40/70
s: 0.0457 - acc: 0.9868 - val loss: 0.9909 - val acc: 0.8761
Epoch 41/70
s: 0.0475 - acc: 0.9865 - val loss: 0.9938 - val acc: 0.8768
Epoch 42/70
s: 0.0453 - acc: 0.9872 - val loss: 0.9964 - val acc: 0.8764
Epoch 43/70
a. 0 04E0
     266. 0 0072 val 1666. 0 0044 val 266. 0 0760
```

```
5: ช.ช45ช - acc: ช.9872 - val toss: ช.9944 - val acc: ช.870ช
Epoch 44/70
130000/130000 [============== ] - 115s 884us/step - los
s: 0.0420 - acc: 0.9881 - val loss: 0.9966 - val acc: 0.8755
Epoch 45/70
s: 0.0408 - acc: 0.9886 - val loss: 0.9931 - val acc: 0.8768
Epoch 46/70
s: 0.0418 - acc: 0.9880 - val loss: 0.9936 - val acc: 0.8774
Epoch 47/70
s: 0.0388 - acc: 0.9888 - val loss: 1.0055 - val acc: 0.8751
Epoch 48/70
s: 0.0414 - acc: 0.9884 - val loss: 0.9978 - val acc: 0.8783
Epoch 49/70
s: 0.0387 - acc: 0.9893 - val loss: 1.0141 - val acc: 0.8774
Epoch 50/70
s: 0.0405 - acc: 0.9888 - val loss: 1.0102 - val acc: 0.8760
Epoch 51/70
s: 0.0400 - acc: 0.9889 - val loss: 1.0148 - val acc: 0.8767
Epoch 52/70
s: 0.0371 - acc: 0.9895 - val loss: 1.0072 - val acc: 0.8789
Epoch 53/70
s: 0.0375 - acc: 0.9896 - val loss: 1.0324 - val acc: 0.8762
Epoch 54/70
s: 0.0397 - acc: 0.9888 - val loss: 1.0212 - val acc: 0.8770
Epoch 55/70
s: 0.0376 - acc: 0.9896 - val loss: 1.0132 - val acc: 0.8767
Epoch 56/70
a. 0 0270
     acc. 0 0002 val locc. 1 0211 val acc. 0 0700
```

```
S: U.U3/9 - acc: U.9δ93 - Val lOSS: 1.UZ11 - Val acc: U.δ/δU
Epoch 57/70
s: 0.0375 - acc: 0.9895 - val loss: 1.0294 - val acc: 0.8768
Epoch 58/70
s: 0.0353 - acc: 0.9898 - val loss: 1.0155 - val acc: 0.8765
Epoch 59/70
s: 0.0355 - acc: 0.9902 - val loss: 1.0221 - val acc: 0.8764
Epoch 60/70
s: 0.0349 - acc: 0.9905 - val loss: 1.0265 - val acc: 0.8779
Epoch 61/70
s: 0.0355 - acc: 0.9902 - val loss: 1.0188 - val acc: 0.8773
Epoch 62/70
s: 0.0344 - acc: 0.9906 - val loss: 1.0290 - val acc: 0.8767
Epoch 63/70
s: 0.0333 - acc: 0.9909 - val loss: 1.0305 - val acc: 0.8785
Epoch 64/70
s: 0.0352 - acc: 0.9905 - val loss: 1.0466 - val acc: 0.8743
Epoch 65/70
s: 0.0347 - acc: 0.9904 - val loss: 1.0349 - val acc: 0.8759
Epoch 66/70
s: 0.0330 - acc: 0.9911 - val loss: 1.0333 - val acc: 0.8774
Epoch 67/70
s: 0.0332 - acc: 0.9908 - val loss: 1.0315 - val acc: 0.8770
Epoch 68/70
s: 0.0330 - acc: 0.9910 - val loss: 1.0360 - val acc: 0.8773
Epoch 69/70
```

```
S: ʊ.ʊɔzʊ - acc: ʊ.७७10 - vat_toss: 1.ʊzz4 - vat_acc: ʊ.७/ठ०
        Epoch 70/70
        s: 0.0325 - acc: 0.9912 - val loss: 1.0297 - val acc: 0.8781
In [24]: import matplotlib.pyplot as plt
        scores = model.evaluate(testarray1, testy, verbose=0)
        print("Accuracy: %.2f%" % (scores[1]*100))
        # Test and train accuracy of the model
        model 3 test = scores[1]
        model 3 train = max(history.history['acc'])
        # Plotting Train and Test Loss VS no. of epochs
        # list of epoch numbers
        x = list(range(1,71))
        # Validation loss
        vy = history.history['val loss']
        # Training loss
        ty = history.history['loss']
        # Calling the function to draw the plot
        plt dynamic(x, vy, ty)
        Accuracy: 87.81%
```



```
In [25]: import keras as keras
         import tensorflow as tf
         from keras.models import Sequential
         from keras.layers import Dense,Dropout,Flatten,BatchNormalization
         from keras.layers import Conv1D, MaxPooling1D
         from keras.layers import LSTM
         model=Sequential()
         model.add(Conv1D(300,kernel_size=(26),activation='relu',input_shape=(20)
         0,26)))
         model.add(MaxPooling1D(pool size=2))
         model.add(Dropout(0.7))
         model.add(BatchNormalization())
         model.add(Conv1D(250,26,activation='relu'))
         model.add(MaxPooling1D(pool size=4))
         model.add(Dropout(0.7))
         model.add(BatchNormalization())
         model.add(LSTM(500,dropout=0.4,return sequences=True))
         model.add(BatchNormalization())
```

```
model.add(Flatten())
model.add(Dense(11180,activation='softmax'))
model.compile(loss=keras.losses.sparse categorical crossentropy,optimiz
er='adam',metrics=['accuracy'])
history=model.fit(trainarray1,trainy,epochs=70,validation data=[testarr
ay1, testy], batch size=256)
W0619 08:12:08.018236 139960010635136 nn ops.py:4224] Large dropout rat
e: 0.7 (>0.5). In TensorFlow 2.x, dropout() uses dropout rate instead o
f keep prob. Please ensure that this is intended.
W0619 08:12:08.141388 139960010635136 nn ops.py:4224] Large dropout rat
e: 0.7 (>0.5). In TensorFlow 2.x, dropout() uses dropout rate instead o
f keep prob. Please ensure that this is intended.
Train on 130000 samples, validate on 20000 samples
Epoch 1/70
s: 6.0865 - acc: 0.1738 - val loss: 2.9649 - val acc: 0.4763
Epoch 2/70
s: 2.6262 - acc: 0.5068 - val loss: 1.6330 - val acc: 0.6788
Epoch 3/70
s: 1.4468 - acc: 0.6791 - val loss: 1.2906 - val acc: 0.7484
Epoch 4/70
s: 0.9376 - acc: 0.7732 - val loss: 1.1468 - val acc: 0.7808
Epoch 5/70
s: 0.6741 - acc: 0.8260 - val loss: 1.1004 - val acc: 0.7991
Epoch 6/70
s: 0.5243 - acc: 0.8610 - val loss: 1.0694 - val acc: 0.8101
Epoch 7/70
s: 0.4319 - acc: 0.8832 - val loss: 1.0478 - val acc: 0.8183
Epoch 8/70
s: 0.3615 - acc: 0.8987 - val loss: 1.0683 - val acc: 0.8242
Epoch 9/70
```

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```
s: 0.3156 - acc: 0.9107 - val loss: 1.0538 - val acc: 0.8271
Epoch 10/70
s: 0.2759 - acc: 0.9220 - val loss: 1.0504 - val acc: 0.8314
Epoch 11/70
s: 0.2455 - acc: 0.9296 - val loss: 1.0662 - val acc: 0.8348
Epoch 12/70
s: 0.2253 - acc: 0.9351 - val loss: 1.0562 - val acc: 0.8360
Epoch 13/70
s: 0.2059 - acc: 0.9404 - val loss: 1.0502 - val acc: 0.8389
Epoch 14/70
s: 0.1910 - acc: 0.9442 - val loss: 1.0618 - val acc: 0.8393
Epoch 15/70
s: 0.1692 - acc: 0.9512 - val loss: 1.0514 - val acc: 0.8467
Epoch 16/70
s: 0.1658 - acc: 0.9523 - val loss: 1.0507 - val acc: 0.8464
Epoch 17/70
s: 0.1497 - acc: 0.9559 - val loss: 1.0728 - val acc: 0.8437
Epoch 18/70
s: 0.1421 - acc: 0.9586 - val loss: 1.0778 - val acc: 0.8433
Epoch 19/70
s: 0.1358 - acc: 0.9604 - val loss: 1.0748 - val acc: 0.8454
Epoch 20/70
s: 0.1287 - acc: 0.9622 - val loss: 1.0761 - val acc: 0.8488
Epoch 21/70
s: 0.1239 - acc: 0.9639 - val loss: 1.0911 - val acc: 0.8467
Epoch 22/70
```

```
s: 0.1145 - acc: 0.9669 - val loss: 1.0812 - val acc: 0.8502
Epoch 23/70
s: 0.1107 - acc: 0.9681 - val loss: 1.0889 - val acc: 0.8484
Epoch 24/70
s: 0.1077 - acc: 0.9683 - val loss: 1.0920 - val acc: 0.8486
Epoch 25/70
s: 0.1056 - acc: 0.9692 - val loss: 1.0778 - val acc: 0.8505
Epoch 26/70
s: 0.0990 - acc: 0.9709 - val_loss: 1.0583 - val_acc: 0.8531
Epoch 27/70
s: 0.0918 - acc: 0.9732 - val loss: 1.0762 - val acc: 0.8525
Epoch 28/70
s: 0.0900 - acc: 0.9738 - val loss: 1.0879 - val acc: 0.8531
Epoch 29/70
s: 0.0870 - acc: 0.9744 - val loss: 1.0883 - val acc: 0.8520
Epoch 30/70
s: 0.0848 - acc: 0.9748 - val loss: 1.0937 - val acc: 0.8540
Epoch 31/70
s: 0.0816 - acc: 0.9762 - val loss: 1.1076 - val acc: 0.8522
Epoch 32/70
s: 0.0781 - acc: 0.9770 - val loss: 1.0945 - val acc: 0.8540
Epoch 33/70
s: 0.0756 - acc: 0.9777 - val loss: 1.1066 - val acc: 0.8551
Epoch 34/70
s: 0.0736 - acc: 0.9787 - val loss: 1.1017 - val acc: 0.8542
Epoch 35/70
```

```
s: 0.0692 - acc: 0.9798 - val loss: 1.0889 - val acc: 0.8565
Epoch 36/70
s: 0.0714 - acc: 0.9790 - val loss: 1.0994 - val acc: 0.8564
Epoch 37/70
s: 0.0669 - acc: 0.9806 - val loss: 1.1082 - val acc: 0.8535
Epoch 38/70
s: 0.0644 - acc: 0.9809 - val loss: 1.1136 - val acc: 0.8553
Epoch 39/70
130000/130000 [=============== ] - 112s 863us/step - los
s: 0.0633 - acc: 0.9818 - val_loss: 1.1184 - val_acc: 0.8539
Epoch 40/70
s: 0.0625 - acc: 0.9819 - val loss: 1.1116 - val acc: 0.8560
Epoch 41/70
s: 0.0613 - acc: 0.9822 - val loss: 1.1049 - val acc: 0.8569
Epoch 42/70
s: 0.0585 - acc: 0.9829 - val loss: 1.1242 - val acc: 0.8568
Epoch 43/70
s: 0.0573 - acc: 0.9835 - val loss: 1.1039 - val acc: 0.8563
Epoch 44/70
s: 0.0559 - acc: 0.9837 - val loss: 1.1024 - val acc: 0.8577
Epoch 45/70
s: 0.0551 - acc: 0.9837 - val loss: 1.1113 - val acc: 0.8573
Epoch 46/70
s: 0.0546 - acc: 0.9841 - val loss: 1.1059 - val acc: 0.8549
Epoch 47/70
s: 0.0535 - acc: 0.9846 - val loss: 1.1075 - val acc: 0.8538
Epoch 48/70
```

```
s: 0.0534 - acc: 0.9845 - val loss: 1.1074 - val acc: 0.8593
Epoch 49/70
s: 0.0494 - acc: 0.9859 - val loss: 1.0916 - val acc: 0.8588
Epoch 50/70
s: 0.0510 - acc: 0.9851 - val loss: 1.1015 - val acc: 0.8562
Epoch 51/70
s: 0.0468 - acc: 0.9864 - val loss: 1.1149 - val acc: 0.8555
Epoch 52/70
130000/130000 [============== ] - 112s 861us/step - los
s: 0.0487 - acc: 0.9859 - val_loss: 1.0895 - val_acc: 0.8601
Epoch 53/70
s: 0.0474 - acc: 0.9864 - val loss: 1.1081 - val acc: 0.8601
Epoch 54/70
s: 0.0458 - acc: 0.9865 - val loss: 1.1379 - val acc: 0.8556
Epoch 55/70
s: 0.0443 - acc: 0.9873 - val loss: 1.1161 - val acc: 0.8578
Epoch 56/70
s: 0.0459 - acc: 0.9868 - val loss: 1.1063 - val acc: 0.8588
Epoch 57/70
s: 0.0441 - acc: 0.9872 - val loss: 1.1033 - val acc: 0.8586
Epoch 58/70
s: 0.0437 - acc: 0.9875 - val loss: 1.1107 - val acc: 0.8595
Epoch 59/70
s: 0.0416 - acc: 0.9879 - val loss: 1.1113 - val acc: 0.8606
Epoch 60/70
s: 0.0416 - acc: 0.9879 - val loss: 1.1092 - val acc: 0.8613
Epoch 61/70
```

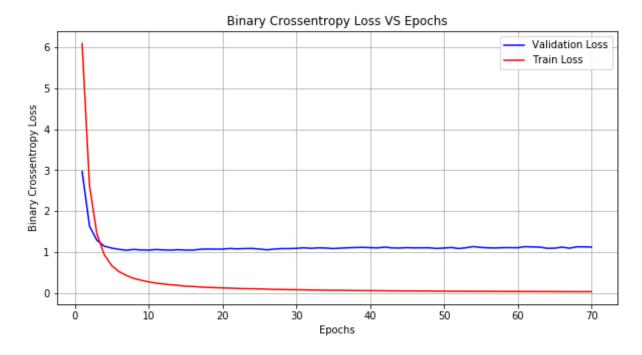
```
s: 0.0407 - acc: 0.9884 - val loss: 1.1364 - val acc: 0.8575
     Epoch 62/70
     s: 0.0413 - acc: 0.9880 - val loss: 1.1274 - val acc: 0.8563
     Epoch 63/70
     s: 0.0401 - acc: 0.9882 - val loss: 1.1242 - val acc: 0.8586
     Epoch 64/70
     s: 0.0392 - acc: 0.9888 - val loss: 1.0945 - val acc: 0.8604
     Epoch 65/70
     s: 0.0390 - acc: 0.9887 - val loss: 1.0978 - val acc: 0.8631
     Epoch 66/70
     s: 0.0372 - acc: 0.9893 - val loss: 1.1241 - val acc: 0.8603
     Epoch 67/70
     s: 0.0378 - acc: 0.9892 - val loss: 1.0979 - val acc: 0.8629
     Epoch 68/70
     s: 0.0365 - acc: 0.9894 - val loss: 1.1314 - val acc: 0.8572
     Epoch 69/70
     s: 0.0368 - acc: 0.9892 - val loss: 1.1309 - val acc: 0.8585
     Epoch 70/70
     s: 0.0379 - acc: 0.9888 - val loss: 1.1260 - val acc: 0.8600
In [26]: import matplotlib.pyplot as plt
     scores = model.evaluate(testarray1,testy, verbose=0)
     print("Accuracy: %.2f%" % (scores[1]*100))
     # Test and train accuracy of the model
     model 3 test = scores[1]
     model 3 train = max(history.history['acc'])
     # Plotting Train and Test Loss VS no. of epochs
```

```
# list of epoch numbers
x = list(range(1,71))

# Validation loss
vy = history.history['val_loss']
# Training loss
ty = history.history['loss']

# Calling the function to draw the plot
plt_dynamic(x, vy, ty)
```

Accuracy: 86.00%



```
In [25]: import keras as keras
import tensorflow as tf
from keras.models import Sequential
from keras.layers import Dense,Dropout,Flatten,BatchNormalization
from keras.layers import Conv1D,MaxPooling1D
```

```
from keras.layers import LSTM, Bidirectional
       model=Sequential()
       model.add(Dense(256,activation='relu',input shape=(200,26)))
       model.add(Dropout(0.7))
       model.add(BatchNormalization())
       model.add(Bidirectional(LSTM(26,dropout=0.5,return sequences=True)))
       model.add(BatchNormalization())
       model.add(Flatten())
       model.add(Dense(11180,activation='softmax'))
       model.compile(loss=keras.losses.sparse categorical crossentropy,optimiz
       er='adam',metrics=['accuracy'])
       history=model.fit(trainarray1,trainy,epochs=5,validation data=[testarra
       y1, testy], batch size=128)
       W0619 20:24:43.532114 140629908809600 nn ops.py:4224] Large dropout rat
       e: 0.7 (>0.5). In TensorFlow 2.x, dropout() uses dropout rate instead o
       f keep prob. Please ensure that this is intended.
       Train on 130000 samples, validate on 20000 samples
       Epoch 1/5
       3.7448 - acc: 0.5683 - val loss: 0.8746 - val acc: 0.8793
       Epoch 2/5
       0.2431 - acc: 0.9697 - val loss: 0.8588 - val acc: 0.8860
       Epoch 3/5
       0.1112 - acc: 0.9911 - val loss: 0.8922 - val acc: 0.8881
       Epoch 4/5
       0.1043 - acc: 0.9925 - val loss: 0.9823 - val acc: 0.8818
       Epoch 5/5
       0.1062 - acc: 0.9915 - val loss: 1.1620 - val acc: 0.8638
In [27]: import matplotlib.pyplot as plt
       scores = model.evaluate(testarray1, testy, verbose=0)
       print("Accuracy: %.2f%" % (scores[1]*100))
```

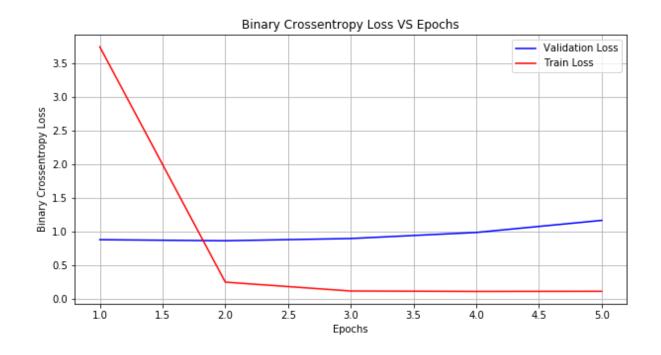
```
# Test and train accuracy of the model
model_3_test = scores[1]
model_3_train = max(history.history['acc'])

# Plotting Train and Test Loss VS no. of epochs
# list of epoch numbers
x = list(range(1,6))

# Validation loss
vy = history.history['val_loss']
# Training loss
ty = history.history['loss']

# Calling the function to draw the plot
plt_dynamic(x, vy, ty)
```

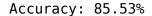
Accuracy: 86.38%

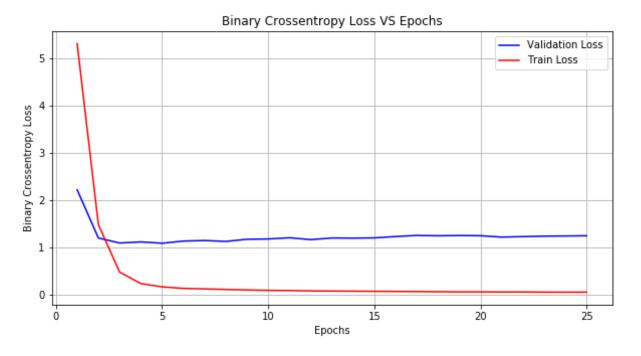


```
In [0]: import keras as keras
      import tensorflow as tf
      from keras.models import Sequential
      from keras.layers import Dense,Dropout,Flatten,BatchNormalization
      from keras.layers import Conv1D, MaxPooling1D
      model=Sequential()
      model.add(Conv1D(100,kernel size=10,activation='relu',input shape=(200,
      26)))
      model.add(MaxPooling1D(pool size=2))
      model.add(Dropout(0.2))
      model.add(Conv1D(250,20,activation='relu'))
      model.add(MaxPooling1D(pool size=4))
      model.add(Dropout(0.2))
      model.add(BatchNormalization())
      model.add(Flatten())
      model.add(Dense(11180,activation='softmax'))
      model.compile(loss=keras.losses.sparse categorical crossentropy,optimiz
      er='adam',metrics=['accuracy'])
      history=model.fit(trainarray1,trainy,epochs=25,validation data=[testarr
      ay1, testy], batch size=256)
      Train on 115275 samples, validate on 21113 samples
      Epoch 1/25
      5.3151 - acc: 0.2801 - val loss: 2.2157 - val acc: 0.6586
      Epoch 2/25
      1.4764 - acc: 0.7387 - val loss: 1.1932 - val acc: 0.8027
      Epoch 3/25
      0.4694 - acc: 0.8962 - val loss: 1.0867 - val acc: 0.8221
      Epoch 4/25
      0.2276 - acc: 0.9449 - val loss: 1.1101 - val acc: 0.8257
      Epoch 5/25
      0.1566 - acc: 0.9601 - val loss: 1.0820 - val acc: 0.8377
      Epoch 6/25
```

```
0.1241 - acc: 0.9668 - val loss: 1.1276 - val acc: 0.8399
Epoch 7/25
0.1139 - acc: 0.9698 - val loss: 1.1402 - val acc: 0.8387
Epoch 8/25
0.1019 - acc: 0.9722 - val loss: 1.1203 - val_acc: 0.8421
Epoch 9/25
0.0911 - acc: 0.9757 - val loss: 1.1661 - val acc: 0.8440
Epoch 10/25
0.0830 - acc: 0.9782 - val loss: 1.1724 - val acc: 0.8444
Epoch 11/25
0.0788 - acc: 0.9793 - val loss: 1.1980 - val acc: 0.8418
Epoch 12/25
0.0710 - acc: 0.9816 - val loss: 1.1586 - val acc: 0.8520
Epoch 13/25
0.0683 - acc: 0.9825 - val loss: 1.1932 - val acc: 0.8500
Epoch 14/25
0.0657 - acc: 0.9831 - val loss: 1.1901 - val acc: 0.8523
Epoch 15/25
0.0627 - acc: 0.9841 - val loss: 1.1953 - val acc: 0.8503
Epoch 16/25
0.0597 - acc: 0.9849 - val loss: 1.2241 - val acc: 0.8511
Epoch 17/25
0.0577 - acc: 0.9855 - val loss: 1.2474 - val acc: 0.8504
Epoch 18/25
0.0534 - acc: 0.9867 - val loss: 1.2401 - val acc: 0.8482
Epoch 19/25
A ASAA - acc: A 0872 - val loss: 1 2454 - val acc: A 85A3
```

```
0.0004 - acc: 0.3014 - Aat (022: 1.5474 - Aat acc: 0.0000
     Epoch 20/25
     0.0499 - acc: 0.9880 - val loss: 1.2413 - val_acc: 0.8538
     Epoch 21/25
     0.0480 - acc: 0.9883 - val loss: 1.2119 - val acc: 0.8576
     Epoch 22/25
     0.0484 - acc: 0.9884 - val loss: 1.2224 - val acc: 0.8580
     Epoch 23/25
     0.0450 - acc: 0.9891 - val loss: 1.2322 - val acc: 0.8582
     Epoch 24/25
     0.0444 - acc: 0.9896 - val loss: 1.2356 - val acc: 0.8557
     Epoch 25/25
     0.0446 - acc: 0.9891 - val loss: 1.2405 - val acc: 0.8553
In [0]: import matplotlib.pyplot as plt
     scores = model.evaluate(testarray1, testy, verbose=0)
     print("Accuracy: %.2f%" % (scores[1]*100))
     # Test and train accuracy of the model
     model 3 test = scores[1]
     model 3 train = max(history.history['acc'])
     # Plotting Train and Test Loss VS no. of epochs
     # list of epoch numbers
     x = list(range(1,26))
     # Validation loss
     vy = history.history['val loss']
     # Training loss
     ty = history.history['loss']
     # Calling the function to draw the plot
     plt dynamic(x, vy, ty)
```





```
In [0]: import keras as keras
   import tensorflow as tf
   from keras.models import Sequential
   from keras.layers import Dense,Dropout,Flatten,BatchNormalization
   from keras.layers import Conv1D,MaxPooling1D
   model=Sequential()
   model.add(Conv1D(2000,kernel_size=26,activation='relu',input_shape=(200,26)))
   model.add(MaxPooling1D(pool_size=2))
   model.add(Dropout(0.4))
   model.add(MaxPooling1D(pool_size=4))
   model.add(MaxPooling1D(pool_size=4))
   model.add(Dropout(0.6))
   model.add(BatchNormalization())
```

```
model.add(Flatten())
model.add(Dense(11180,activation='softmax'))
model.compile(loss=keras.losses.sparse categorical crossentropy,optimiz
er='adam', metrics=['accuracy'])
history=model.fit(trainarray1,trainy,epochs=80,validation data=[testarr
ay1,testy],batch size=128)
W0619 09:23:08.199344 140477795272576 nn ops.py:4224] Large dropout rat
e: 0.6 (>0.5). In TensorFlow 2.x, dropout() uses dropout rate instead o
f keep prob. Please ensure that this is intended.
Train on 130000 samples, validate on 20000 samples
Epoch 1/80
6.7167 - acc: 0.1176 - val loss: 3.9094 - val acc: 0.4072
Epoch 2/80
3.6362 - acc: 0.4200 - val loss: 2.0259 - val acc: 0.6724
Epoch 3/80
2.2216 - acc: 0.5902 - val loss: 1.4423 - val acc: 0.7579
Epoch 4/80
1.5199 - acc: 0.6887 - val loss: 1.1751 - val acc: 0.7984
Epoch 5/80
1.1232 - acc: 0.7518 - val loss: 1.0267 - val acc: 0.8250
Epoch 6/80
0.8600 - acc: 0.7990 - val loss: 0.9646 - val acc: 0.8383
Epoch 7/80
0.6916 - acc: 0.8312 - val loss: 0.9139 - val acc: 0.8487
Epoch 8/80
0.5715 - acc: 0.8562 - val loss: 0.8772 - val acc: 0.8534
Epoch 9/80
0.4941 - acc: 0.8716 - val loss: 0.8622 - val acc: 0.8614
Epoch 10/80
120000/120000 [__
```

```
0.4336 - acc: 0.8860 - val loss: 0.8879 - val acc: 0.8614
Epoch 11/80
0.3850 - acc: 0.8974 - val loss: 0.8403 - val acc: 0.8688
Epoch 12/80
0.3440 - acc: 0.9070 - val loss: 0.8286 - val acc: 0.8694
Epoch 13/80
0.3167 - acc: 0.9134 - val loss: 0.8284 - val acc: 0.8703
Epoch 14/80
0.2980 - acc: 0.9179 - val loss: 0.8511 - val acc: 0.8739
Epoch 15/80
0.2689 - acc: 0.9251 - val loss: 0.8374 - val acc: 0.8747
Epoch 16/80
0.2545 - acc: 0.9290 - val loss: 0.8265 - val acc: 0.8755
Epoch 17/80
0.2384 - acc: 0.9337 - val loss: 0.8368 - val acc: 0.8776
Epoch 18/80
0.2298 - acc: 0.9358 - val loss: 0.8363 - val acc: 0.8791
Epoch 19/80
0.2141 - acc: 0.9396 - val loss: 0.8347 - val acc: 0.8793
Epoch 20/80
0.2060 - acc: 0.9420 - val loss: 0.7848 - val acc: 0.8840
Epoch 21/80
0.1941 - acc: 0.9452 - val loss: 0.7954 - val acc: 0.8847
Epoch 22/80
0.1797 - acc: 0.9490 - val loss: 0.8097 - val acc: 0.8833
Epoch 23/80
120000/120000 [_.
```

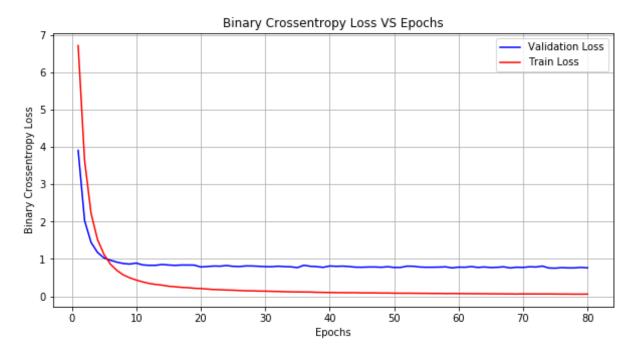
```
0.1750 - acc: 0.9498 - val loss: 0.8052 - val acc: 0.8846
Epoch 24/80
0.1669 - acc: 0.9527 - val loss: 0.8236 - val acc: 0.8843
Epoch 25/80
0.1624 - acc: 0.9542 - val loss: 0.8016 - val acc: 0.8860
Epoch 26/80
0.1533 - acc: 0.9559 - val loss: 0.7958 - val acc: 0.8872
Epoch 27/80
0.1463 - acc: 0.9577 - val loss: 0.8126 - val acc: 0.8881
Epoch 28/80
0.1452 - acc: 0.9583 - val loss: 0.8112 - val acc: 0.8886
Epoch 29/80
0.1389 - acc: 0.9600 - val loss: 0.8024 - val acc: 0.8892
Epoch 30/80
0.1372 - acc: 0.9607 - val loss: 0.7927 - val acc: 0.8890
Epoch 31/80
0.1317 - acc: 0.9622 - val loss: 0.7913 - val acc: 0.8892
Epoch 32/80
0.1281 - acc: 0.9632 - val loss: 0.8051 - val acc: 0.8874
Epoch 33/80
0.1217 - acc: 0.9650 - val loss: 0.7938 - val acc: 0.8917
Epoch 34/80
0.1184 - acc: 0.9660 - val loss: 0.7883 - val acc: 0.8922
Epoch 35/80
0.1155 - acc: 0.9665 - val loss: 0.7669 - val acc: 0.8942
Epoch 36/80
120000/120000 [_.
```

```
0.1140 - acc: 0.9671 - val loss: 0.8297 - val acc: 0.8902
Epoch 37/80
0.1129 - acc: 0.9681 - val loss: 0.8031 - val_acc: 0.8920
Epoch 38/80
0.1057 - acc: 0.9693 - val loss: 0.7931 - val acc: 0.8933
Epoch 39/80
0.1032 - acc: 0.9706 - val loss: 0.7741 - val acc: 0.8950
Epoch 40/80
0.0999 - acc: 0.9722 - val loss: 0.8107 - val acc: 0.8941
Epoch 41/80
0.0974 - acc: 0.9720 - val loss: 0.8019 - val acc: 0.8933
Epoch 42/80
0.0961 - acc: 0.9727 - val loss: 0.8070 - val_acc: 0.8934
Epoch 43/80
0.0943 - acc: 0.9729 - val loss: 0.7963 - val acc: 0.8940
Epoch 44/80
0.0953 - acc: 0.9722 - val loss: 0.7794 - val acc: 0.8941
Epoch 45/80
0.0902 - acc: 0.9739 - val loss: 0.7772 - val acc: 0.8963
Epoch 46/80
0.0903 - acc: 0.9741 - val loss: 0.7836 - val acc: 0.8945
Epoch 47/80
0.0890 - acc: 0.9748 - val loss: 0.7851 - val acc: 0.8959
Epoch 48/80
0.0863 - acc: 0.9752 - val loss: 0.7761 - val acc: 0.8962
Epoch 49/80
120000/120000 [__
```

```
0.0866 - acc: 0.9757 - val loss: 0.7920 - val acc: 0.8957
Epoch 50/80
0.0817 - acc: 0.9764 - val loss: 0.7716 - val acc: 0.8976
Epoch 51/80
0.0817 - acc: 0.9756 - val loss: 0.7723 - val acc: 0.8975
Epoch 52/80
0.0817 - acc: 0.9766 - val loss: 0.8065 - val acc: 0.8940
Epoch 53/80
0.0807 - acc: 0.9768 - val loss: 0.8028 - val acc: 0.8950
Epoch 54/80
0.0781 - acc: 0.9774 - val loss: 0.7828 - val acc: 0.8979
Epoch 55/80
0.0772 - acc: 0.9776 - val loss: 0.7769 - val_acc: 0.8982
Epoch 56/80
0.0743 - acc: 0.9788 - val loss: 0.7777 - val acc: 0.8972
Epoch 57/80
0.0756 - acc: 0.9783 - val loss: 0.7816 - val acc: 0.8982
Epoch 58/80
0.0713 - acc: 0.9793 - val loss: 0.7880 - val acc: 0.8980
Epoch 59/80
0.0736 - acc: 0.9791 - val loss: 0.7590 - val acc: 0.8990
Epoch 60/80
0.0712 - acc: 0.9799 - val loss: 0.7806 - val acc: 0.8994
Epoch 61/80
0.0702 - acc: 0.9799 - val loss: 0.7773 - val acc: 0.9000
Epoch 62/80
120000/120000 [_.
```

```
0.0691 - acc: 0.9806 - val loss: 0.7952 - val acc: 0.8991
Epoch 63/80
0.0678 - acc: 0.9801 - val loss: 0.7714 - val acc: 0.9011
Epoch 64/80
0.0682 - acc: 0.9808 - val loss: 0.7852 - val acc: 0.9001
Epoch 65/80
0.0655 - acc: 0.9810 - val loss: 0.7679 - val acc: 0.8996
Epoch 66/80
0.0650 - acc: 0.9811 - val loss: 0.7763 - val acc: 0.8999
Epoch 67/80
0.0636 - acc: 0.9817 - val loss: 0.7892 - val acc: 0.9008
Epoch 68/80
0.0625 - acc: 0.9818 - val_loss: 0.7571 - val acc: 0.9017
Epoch 69/80
0.0595 - acc: 0.9827 - val loss: 0.7780 - val acc: 0.9005
Epoch 70/80
0.0629 - acc: 0.9819 - val loss: 0.7730 - val acc: 0.9006
Epoch 71/80
0.0623 - acc: 0.9825 - val loss: 0.7901 - val acc: 0.8988
Epoch 72/80
0.0614 - acc: 0.9826 - val loss: 0.7837 - val acc: 0.9005
Epoch 73/80
0.0603 - acc: 0.9830 - val loss: 0.8077 - val acc: 0.8963
Epoch 74/80
0.0621 - acc: 0.9824 - val loss: 0.7569 - val acc: 0.9016
Epoch 75/80
120000/120000 [_.
```

```
0.0593 - acc: 0.9833 - val loss: 0.7522 - val acc: 0.9019
     Epoch 76/80
     0.0587 - acc: 0.9835 - val loss: 0.7670 - val acc: 0.9006
     Epoch 77/80
     0.0584 - acc: 0.9836 - val loss: 0.7596 - val acc: 0.9018
     Epoch 78/80
     0.0559 - acc: 0.9840 - val loss: 0.7602 - val acc: 0.9006
     Epoch 79/80
     0.0564 - acc: 0.9838 - val loss: 0.7728 - val acc: 0.9000
     Epoch 80/80
     0.0574 - acc: 0.9832 - val loss: 0.7615 - val acc: 0.9034
In [0]: import matplotlib.pyplot as plt
     scores = model.evaluate(testarray1, testy, verbose=0)
     print("Accuracy: %.2f%" % (scores[1]*100))
     # Test and train accuracy of the model
     model 3 test = scores[1]
     model 3 train = max(history.history['acc'])
     # Plotting Train and Test Loss VS no. of epochs
     # list of epoch numbers
     x = list(range(1,81))
     # Validation loss
     vy = history.history['val loss']
     # Training loss
     ty = history.history['loss']
     # Calling the function to draw the plot
     plt dynamic(x, vy, ty)
     Accuracy: 90.34%
```



```
In [0]: import keras as keras
        import tensorflow as tf
        from keras.models import Sequential
        from keras.layers import Dense,Dropout,Flatten,BatchNormalization
        from keras.layers import Conv1D, MaxPooling1D
        from keras.layers import LSTM, Bidirectional
        model=Sequential()
        model.add(Dense(256,activation='relu',input shape=(200,26)))
        model.add(Dropout(0.3))
        model.add(BatchNormalization())
        model.add(LSTM(26,dropout=0.2,return sequences=True))
        model.add(BatchNormalization())
        model.add(Flatten())
        model.add(Dense(128,activation='relu',input shape=(200,26)))
        model.add(Dropout(0.3))
        model.add(BatchNormalization())
        model.add(Dense(11180,activation='softmax'))
```

model.compile(loss=keras.losses.sparse_categorical_crossentropy,optimiz
er='adam',metrics=['accuracy'])
history=model.fit(trainarray1,trainy,epochs=60,validation_data=[testarray1,testy],batch_size=128)

WARNING: Logging before flag parsing goes to stderr. W0619 16:14:51.595402 140045008664448 deprecation_wrapper.py:119] From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backen d.py:74: The name tf.get_default_graph is deprecated. Please use tf.com pat.v1.get default graph instead.

W0619 16:14:51.627513 140045008664448 deprecation_wrapper.py:119] From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backen d.py:517: The name tf.placeholder is deprecated. Please use tf.compat.v 1.placeholder instead.

W0619 16:14:51.638072 140045008664448 deprecation_wrapper.py:119] From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backen d.py:4138: The name tf.random_uniform is deprecated. Please use tf.rand om.uniform instead.

W0619 16:14:51.663547 140045008664448 deprecation_wrapper.py:119] From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backen d.py:133: The name tf.placeholder_with_default is deprecated. Please us e tf.compat.v1.placeholder_with_default instead.

W0619 16:14:51.673146 140045008664448 deprecation.py:506] From /usr/loc al/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:344 5: calling dropout (from tensorflow.python.ops.nn_ops) with keep_prob i s deprecated and will be removed in a future version. Instructions for updating:

Please use `rate` instead of `keep_prob`. Rate should be set to `rate = 1 - keep prob`.

W0619 16:14:52.402341 140045008664448 deprecation_wrapper.py:119] From /usr/local/lib/python3.6/dist-packages/keras/optimizers.py:790: The nam e tf.train.Optimizer is deprecated. Please use tf.compat.v1.train.Optimizer instead.

W0619 16:14:52.425379 140045008664448 deprecation_wrapper.py:119] From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backen

```
d.py:3341: The name tf.log is deprecated. Please use tf.math.log instea
d.
W0619 16:14:52.531753 140045008664448 deprecation.py:3231 From /usr/loc
al/lib/python3.6/dist-packages/tensorflow/python/ops/math grad.py:1250:
add dispatch support.<locals>.wrapper (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
Train on 130000 samples, validate on 20000 samples
Epoch 1/60
7.1105 - acc: 0.0813 - val loss: 5.0234 - val acc: 0.3011
Epoch 2/60
4.0551 - acc: 0.3979 - val loss: 2.2129 - val acc: 0.6724
Epoch 3/60
2.1054 - acc: 0.6402 - val loss: 1.2749 - val acc: 0.7995
Epoch 4/60
1.2024 - acc: 0.7645 - val loss: 0.9455 - val acc: 0.8418
Epoch 5/60
0.7732 - acc: 0.8329 - val loss: 0.8285 - val acc: 0.8560
Epoch 6/60
0.5557 - acc: 0.8712 - val loss: 0.7840 - val acc: 0.8620
Epoch 7/60
0.4395 - acc: 0.8931 - val loss: 0.7603 - val acc: 0.8665
Epoch 8/60
0.3698 - acc: 0.9051 - val loss: 0.7541 - val acc: 0.8669
Epoch 9/60
0.3255 - acc: 0.9154 - val loss: 0.7593 - val acc: 0.8695
Epoch 10/60
```

```
0.2862 - acc: 0.9230 - val loss: 0.7505 - val acc: 0.8728
Epoch 11/60
0.2600 - acc: 0.9296 - val loss: 0.7510 - val acc: 0.8728
Epoch 12/60
0.2408 - acc: 0.9343 - val loss: 0.7619 - val acc: 0.8719
Epoch 13/60
0.2261 - acc: 0.9375 - val loss: 0.7672 - val acc: 0.8732
Epoch 14/60
0.2149 - acc: 0.9403 - val loss: 0.7720 - val acc: 0.8720
Epoch 15/60
0.1985 - acc: 0.9444 - val loss: 0.7741 - val acc: 0.8718
Epoch 16/60
0.1896 - acc: 0.9467 - val loss: 0.7699 - val acc: 0.8752
Epoch 17/60
0.1817 - acc: 0.9484 - val loss: 0.7783 - val acc: 0.8742
Epoch 18/60
0.1705 - acc: 0.9515 - val loss: 0.7826 - val acc: 0.8750
Epoch 19/60
0.1637 - acc: 0.9538 - val loss: 0.7891 - val acc: 0.8775
Epoch 20/60
0.1598 - acc: 0.9549 - val loss: 0.7953 - val acc: 0.8738
Epoch 21/60
0.1567 - acc: 0.9551 - val loss: 0.7832 - val acc: 0.8774
Epoch 22/60
0.1511 - acc: 0.9569 - val loss: 0.7959 - val acc: 0.8748
Epoch 23/60
```

```
0.1450 - acc: 0.9580 - val loss: 0.7964 - val acc: 0.8768
Epoch 24/60
0.1406 - acc: 0.9596 - val loss: 0.8018 - val acc: 0.8761
Epoch 25/60
0.1376 - acc: 0.9602 - val loss: 0.8057 - val acc: 0.8779
Epoch 26/60
0.1319 - acc: 0.9614 - val loss: 0.8022 - val acc: 0.8775
Epoch 27/60
0.1293 - acc: 0.9625 - val loss: 0.8029 - val acc: 0.8774
Epoch 28/60
0.1273 - acc: 0.9632 - val loss: 0.8071 - val acc: 0.8779
Epoch 29/60
0.1256 - acc: 0.9640 - val loss: 0.7995 - val acc: 0.8778
Epoch 30/60
0.1164 - acc: 0.9662 - val loss: 0.8161 - val acc: 0.8770
Epoch 31/60
0.1188 - acc: 0.9654 - val loss: 0.8068 - val acc: 0.8780
Epoch 32/60
0.1140 - acc: 0.9662 - val loss: 0.8140 - val acc: 0.8799
Epoch 33/60
0.1124 - acc: 0.9676 - val loss: 0.8021 - val acc: 0.8793
Epoch 34/60
0.1067 - acc: 0.9686 - val loss: 0.8056 - val acc: 0.8797
Epoch 35/60
0.1088 - acc: 0.9679 - val loss: 0.8234 - val acc: 0.8788
Epoch 36/60
```

```
0.1072 - acc: 0.9687 - val loss: 0.8215 - val acc: 0.8774
Epoch 37/60
0.1065 - acc: 0.9687 - val loss: 0.8254 - val acc: 0.8796
Epoch 38/60
0.1149 - acc: 0.9669 - val loss: 0.8336 - val acc: 0.8789
Epoch 39/60
0.1023 - acc: 0.9699 - val loss: 0.8270 - val acc: 0.8800
Epoch 40/60
0.0967 - acc: 0.9714 - val loss: 0.8330 - val acc: 0.8794
Epoch 41/60
0.0959 - acc: 0.9718 - val loss: 0.8277 - val acc: 0.8810
Epoch 42/60
0.0961 - acc: 0.9715 - val loss: 0.8361 - val acc: 0.8769
Epoch 43/60
0.0930 - acc: 0.9725 - val loss: 0.8367 - val acc: 0.8816
Epoch 44/60
0.0947 - acc: 0.9728 - val loss: 0.8306 - val acc: 0.8809
Epoch 45/60
0.0918 - acc: 0.9731 - val loss: 0.8391 - val acc: 0.8805
Epoch 46/60
0.0873 - acc: 0.9743 - val loss: 0.8397 - val acc: 0.8806
Epoch 47/60
0.0902 - acc: 0.9736 - val loss: 0.8352 - val acc: 0.8816
Epoch 48/60
0.0867 - acc: 0.9742 - val loss: 0.8360 - val acc: 0.8820
Epoch 49/60
```

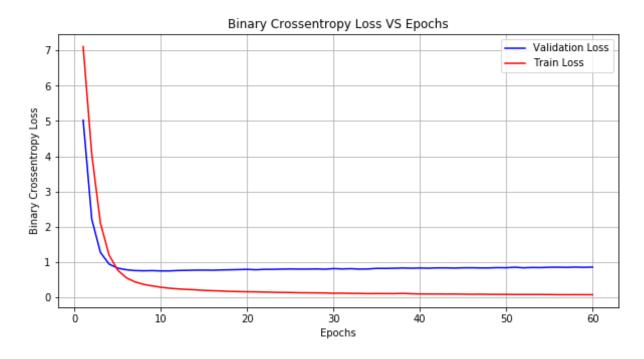
```
0.0852 - acc: 0.9743 - val loss: 0.8438 - val acc: 0.8806
     Epoch 50/60
     0.0852 - acc: 0.9750 - val loss: 0.8409 - val_acc: 0.8825
     Epoch 51/60
     0.0812 - acc: 0.9756 - val loss: 0.8556 - val acc: 0.8812
     Epoch 52/60
     0.0824 - acc: 0.9757 - val loss: 0.8384 - val acc: 0.8831
     Epoch 53/60
     0.0816 - acc: 0.9764 - val loss: 0.8481 - val acc: 0.8814
     Epoch 54/60
     0.0813 - acc: 0.9758 - val loss: 0.8457 - val acc: 0.8817
     Epoch 55/60
     0.0806 - acc: 0.9763 - val loss: 0.8539 - val acc: 0.8822
     Epoch 56/60
     0.0771 - acc: 0.9778 - val loss: 0.8569 - val acc: 0.8811
     Epoch 57/60
     0.0762 - acc: 0.9775 - val loss: 0.8511 - val acc: 0.8827
     Epoch 58/60
     29056/130000 [=====>.....] - ETA: 4:18 - loss: 0.06
     58 - acc: 0.9801Buffered data was truncated after reaching the output s
     ize limit.
In [0]: import matplotlib.pyplot as plt
     scores = model.evaluate(testarray1, testy, verbose=0)
     print("Accuracy: %.2f%" % (scores[1]*100))
     # Test and train accuracy of the model
     model 3 test = scores[1]
     model 3 train = max(history.history['acc'])
```

```
# Plotting Train and Test Loss VS no. of epochs
# list of epoch numbers
x = list(range(1,61))

# Validation loss
vy = history.history['val_loss']
# Training loss
ty = history.history['loss']

# Calling the function to draw the plot
plt_dynamic(x, vy, ty)
```

Accuracy: 88.17%



```
In [0]: import keras as keras
import tensorflow as tf
from keras.models import Sequential
from keras.layers import Dense,Dropout,Flatten,BatchNormalization
```

```
from keras.layers import Conv1D, MaxPooling1D
model=Sequential()
model.add(Conv1D(100,kernel size=10,activation='relu',input shape=(200,
26)))
model.add(MaxPooling1D(pool size=2))
model.add(Dropout(0.2))
model.add(Conv1D(250,20,activation='relu'))
model.add(MaxPooling1D(pool size=4))
model.add(Dropout(0.2))
model.add(BatchNormalization())
model.add(Flatten())
model.add(Dense(11180,activation='softmax'))
model.compile(loss=keras.losses.sparse categorical crossentropy,optimiz
er='adam',metrics=['accuracy'])
history=model.fit(trainarray1,trainy,epochs=25,validation data=[testarr
av1, testy], batch size=256)
WARNING: Logging before flag parsing goes to stderr.
W0618 13:48:12.199924 140483376052096 deprecation wrapper.py:119] From
/usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow backen
d.py:74: The name tf.get default graph is deprecated. Please use tf.com
pat.vl.get_default graph instead.
W0618 13:48:12.241334 140483376052096 deprecation wrapper.py:119] From
/usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow backen
d.py:517: The name tf.placeholder is deprecated. Please use tf.compat.v
1.placeholder instead.
W0618 13:48:12.250728 140483376052096 deprecation wrapper.py:119] From
/usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow backen
d.py:4138: The name tf.random uniform is deprecated. Please use tf.rand
om.uniform instead.
W0618 13:48:12.290457 140483376052096 deprecation wrapper.py:119] From
/usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow backen
d.py:3976: The name tf.nn.max pool is deprecated. Please use tf.nn.max
pool2d instead.
W0618 13:48:12.305730 140483376052096 deprecation wrapper.py:119] From
```

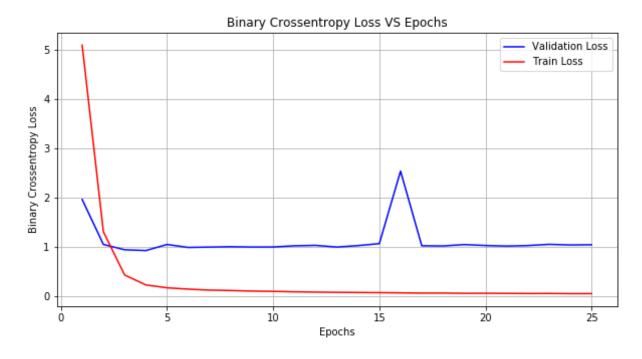
/usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow backen d.py:133: The name tf.placeholder with default is deprecated. Please us e tf.compat.v1.placeholder with default instead. W0618 13:48:12.314735 140483376052096 deprecation.py:5061 From /usr/loc al/lib/python3.6/dist-packages/keras/backend/tensorflow backend.py:344 5: calling dropout (from tensorflow.python.ops.nn ops) with keep prob i s deprecated and will be removed in a future version. Instructions for updating: Please use `rate` instead of `keep prob`. Rate should be set to `rate = 1 - keep prob`. W0618 13:48:12.492441 140483376052096 deprecation wrapper.py:119] From /usr/local/lib/python3.6/dist-packages/keras/optimizers.py:790: The nam e tf.train.Optimizer is deprecated. Please use tf.compat.v1.train.Optim izer instead. W0618 13:48:12.514500 140483376052096 deprecation wrapper.py:119] From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow backen d.py:3341: The name tf.log is deprecated. Please use tf.math.log instea d. W0618 13:48:12.617041 140483376052096 deprecation.py:323] From /usr/loc al/lib/python3.6/dist-packages/tensorflow/python/ops/math grad.py:1250: add dispatch support.<locals>.wrapper (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 Train on 130000 samples, validate on 20000 samples Epoch 1/25 130000/130000 [============] - 77s 591us/step - loss: 5.1009 - acc: 0.3052 - val loss: 1.9616 - val acc: 0.6892 Epoch 2/25 1.3050 - acc: 0.7648 - val loss: 1.0471 - val acc: 0.8212 Epoch 3/25 0.4258 - acc: 0.9047 - val loss: 0.9388 - val acc: 0.8430 Epoch 4/25

```
0.2238 - acc: 0.9454 - val loss: 0.9228 - val acc: 0.8507
Epoch 5/25
0.1656 - acc: 0.9579 - val loss: 1.0461 - val acc: 0.8388
Epoch 6/25
0.1384 - acc: 0.9646 - val loss: 0.9860 - val acc: 0.8503
Epoch 7/25
0.1185 - acc: 0.9691 - val loss: 0.9931 - val acc: 0.8566
Epoch 8/25
0.1103 - acc: 0.9708 - val loss: 1.0009 - val acc: 0.8611
Epoch 9/25
0.0987 - acc: 0.9747 - val loss: 0.9943 - val acc: 0.8600
Epoch 10/25
0.0927 - acc: 0.9766 - val loss: 0.9953 - val acc: 0.8648
Epoch 11/25
0.0841 - acc: 0.9788 - val loss: 1.0196 - val acc: 0.8641
Epoch 12/25
0.0777 - acc: 0.9808 - val loss: 1.0280 - val acc: 0.8656
Epoch 13/25
0.0733 - acc: 0.9819 - val loss: 0.9936 - val acc: 0.8682
Epoch 14/25
0.0699 - acc: 0.9831 - val loss: 1.0235 - val acc: 0.8646
Epoch 15/25
0.0669 - acc: 0.9834 - val loss: 1.0636 - val acc: 0.8653
Epoch 16/25
0.0622 - acc: 0.9855 - val loss: 2.5383 - val acc: 0.7006
Epoch 17/25
```

```
0.0579 - acc: 0.9864 - val loss: 1.0205 - val acc: 0.8738
     Epoch 18/25
     0.0579 - acc: 0.9866 - val loss: 1.0162 - val acc: 0.8747
     Epoch 19/25
     0.0531 - acc: 0.9878 - val loss: 1.0443 - val acc: 0.8726
     Epoch 20/25
     0.0540 - acc: 0.9874 - val loss: 1.0252 - val acc: 0.8741
     Epoch 21/25
     0.0522 - acc: 0.9881 - val loss: 1.0139 - val acc: 0.8741
     Epoch 22/25
     0.0489 - acc: 0.9892 - val loss: 1.0241 - val acc: 0.8778
     Epoch 23/25
     0.0502 - acc: 0.9888 - val loss: 1.0487 - val acc: 0.8726
     Epoch 24/25
     130000/130000 [============ ] - 69s 529us/step - loss:
     0.0464 - acc: 0.9900 - val loss: 1.0362 - val acc: 0.8773
     Epoch 25/25
     0.0469 - acc: 0.9899 - val loss: 1.0409 - val acc: 0.8772
In [0]: import matplotlib.pyplot as plt
     scores = model.evaluate(testarray1, testy, verbose=0)
     print("Accuracy: %.2f%" % (scores[1]*100))
     # Test and train accuracy of the model
     model 3 test = scores[1]
     model 3 train = max(history.history['acc'])
     # Plotting Train and Test Loss VS no. of epochs
     # list of epoch numbers
     x = list(range(1,26))
```

```
# Validation loss
vy = history.history['val_loss']
# Training loss
ty = history.history['loss']
# Calling the function to draw the plot
plt_dynamic(x, vy, ty)
```

Accuracy: 87.72%



```
In [0]: import keras as keras
import tensorflow as tf
from keras.models import Sequential
from keras.layers import Dense,Dropout,Flatten,BatchNormalization
from keras.layers import Conv1D,MaxPooling1D
model=Sequential()
model.add(Conv1D(100,kernel_size=25,activation='relu',input_shape=(200, 26)))
```

```
model.add(MaxPooling1D(pool size=2))
model.add(Dropout(0.2))
model.add(Conv1D(250,26,activation='relu'))
model.add(MaxPooling1D(pool size=4))
model.add(Dropout(0.3))
model.add(BatchNormalization())
model.add(Flatten())
model.add(Dense(11180,activation='softmax'))
model.compile(loss=keras.losses.sparse categorical crossentropy,optimiz
er='adam',metrics=['accuracy'])
history=model.fit(trainarray1,trainy,epochs=55,validation data=[testarr
ay1, testy], batch size=64)
Train on 130000 samples, validate on 20000 samples
Epoch 1/80
5.9637 - acc: 0.1907 - val loss: 2.9397 - val acc: 0.5316
Epoch 2/80
2.6973 - acc: 0.5357 - val loss: 1.5884 - val acc: 0.7259
Epoch 3/80
130000/130000 [============ ] - 95s 728us/step - loss:
1.5215 - acc: 0.6920 - val loss: 1.2224 - val acc: 0.7853
Epoch 4/80
1.0194 - acc: 0.7727 - val loss: 1.0830 - val acc: 0.8136
Epoch 5/80
0.7519 - acc: 0.8211 - val loss: 1.0255 - val acc: 0.8237
Epoch 6/80
0.6017 - acc: 0.8516 - val loss: 0.9725 - val acc: 0.8367
Epoch 7/80
0.5003 - acc: 0.8719 - val loss: 0.9515 - val acc: 0.8442
Epoch 8/80
0.4340 - acc: 0.8874 - val loss: 0.9436 - val acc: 0.8474
```

```
Epoch 9/80
0.3851 - acc: 0.8985 - val loss: 0.9444 - val acc: 0.8515
Epoch 10/80
0.3467 - acc: 0.9069 - val loss: 0.9340 - val acc: 0.8546
Epoch 11/80
0.3239 - acc: 0.9135 - val loss: 0.9380 - val acc: 0.8571
Epoch 12/80
0.2959 - acc: 0.9198 - val loss: 0.9285 - val acc: 0.8603
Epoch 13/80
0.2776 - acc: 0.9250 - val loss: 0.9277 - val acc: 0.8610
Epoch 14/80
0.2538 - acc: 0.9308 - val loss: 0.9311 - val acc: 0.8636
Epoch 15/80
0.2433 - acc: 0.9337 - val loss: 0.9091 - val acc: 0.8671
Epoch 16/80
0.2336 - acc: 0.9363 - val loss: 0.9291 - val acc: 0.8642
Epoch 17/80
0.2204 - acc: 0.9397 - val loss: 0.9106 - val acc: 0.8659
Epoch 18/80
0.2116 - acc: 0.9431 - val loss: 0.8966 - val acc: 0.8700
Epoch 19/80
0.2009 - acc: 0.9450 - val loss: 0.9074 - val acc: 0.8717
Epoch 20/80
0.1941 - acc: 0.9463 - val loss: 0.8932 - val acc: 0.8721
Epoch 21/80
0.1859 - acc: 0.9489 - val loss: 0.9019 - val acc: 0.8721
Enach 22/00
```

```
EDOCII 77/90
0.1826 - acc: 0.9501 - val loss: 0.8993 - val acc: 0.8744
Epoch 23/80
0.1741 - acc: 0.9526 - val loss: 0.9086 - val acc: 0.8718
Epoch 24/80
0.1663 - acc: 0.9544 - val loss: 0.8825 - val acc: 0.8750
Epoch 25/80
0.1666 - acc: 0.9545 - val loss: 0.8968 - val acc: 0.8749
Epoch 26/80
0.1564 - acc: 0.9572 - val loss: 0.8901 - val acc: 0.8753
Epoch 27/80
0.1568 - acc: 0.9572 - val loss: 0.8926 - val acc: 0.8768
Epoch 28/80
0.1505 - acc: 0.9592 - val loss: 0.8964 - val acc: 0.8769
Epoch 29/80
0.1443 - acc: 0.9610 - val loss: 0.8780 - val acc: 0.8797
Epoch 30/80
0.1426 - acc: 0.9609 - val loss: 0.9063 - val acc: 0.8762
Epoch 31/80
0.1384 - acc: 0.9620 - val loss: 0.8973 - val acc: 0.8783
Epoch 32/80
0.1329 - acc: 0.9632 - val loss: 0.8948 - val acc: 0.8797
Epoch 33/80
0.1314 - acc: 0.9639 - val loss: 0.8832 - val acc: 0.8812
Epoch 34/80
0.1264 - acc: 0.9650 - val loss: 0.8835 - val acc: 0.8800
Enach 25/00
```

```
EDOCII 22/00
0.1274 - acc: 0.9652 - val loss: 0.8742 - val acc: 0.8829
Epoch 36/80
0.1214 - acc: 0.9669 - val loss: 0.8891 - val acc: 0.8798
Epoch 37/80
0.1245 - acc: 0.9657 - val loss: 0.8730 - val acc: 0.8835
Epoch 38/80
0.1195 - acc: 0.9673 - val loss: 0.8715 - val acc: 0.8819
Epoch 39/80
0.1151 - acc: 0.9684 - val loss: 0.8703 - val acc: 0.8832
Epoch 40/80
0.1134 - acc: 0.9693 - val loss: 0.8643 - val acc: 0.8832
Epoch 41/80
0.1143 - acc: 0.9688 - val loss: 0.8697 - val acc: 0.8839
Epoch 42/80
0.1094 - acc: 0.9702 - val loss: 0.8668 - val acc: 0.8849
Epoch 43/80
0.1075 - acc: 0.9708 - val loss: 0.8576 - val acc: 0.8841
Epoch 44/80
0.1071 - acc: 0.9713 - val loss: 0.8601 - val acc: 0.8844
Epoch 45/80
0.1053 - acc: 0.9715 - val loss: 0.8715 - val acc: 0.8850
Epoch 46/80
0.1056 - acc: 0.9716 - val loss: 0.8693 - val acc: 0.8855
Epoch 47/80
0.1004 - acc: 0.9729 - val loss: 0.8746 - val acc: 0.8846
Enach 10/00
```

```
בטטכוו 40/00
     0.0994 - acc: 0.9732 - val loss: 0.8684 - val acc: 0.8840
     Epoch 49/80
     0.0980 - acc: 0.9735 - val loss: 0.8739 - val acc: 0.8850
     Epoch 50/80
     130000/130000 [============ ] - 96s 735us/step - loss:
     0.0977 - acc: 0.9738 - val loss: 0.8547 - val acc: 0.8856
     Epoch 51/80
     0.0971 - acc: 0.9738 - val loss: 0.8667 - val acc: 0.8857
     Epoch 52/80
     0.0942 - acc: 0.9743 - val loss: 0.8669 - val acc: 0.8850
     Epoch 53/80
     130000/130000 [============ ] - 96s 735us/step - loss:
     0.0946 - acc: 0.9745 - val loss: 0.8598 - val acc: 0.8870
     Epoch 54/80
     0.0934 - acc: 0.9749 - val loss: 0.8530 - val acc: 0.8872
     Epoch 55/80
     0.0902 - acc: 0.9759 - val loss: 0.8600 - val acc: 0.8869
     Epoch 56/80
     0.0914 - acc: 0.9755 - val loss: 0.8576 - val acc: 0.8897
     Epoch 57/80
      83776/130000 [==========>.....] - ETA: 33s - loss: 0.088
     3 - acc: 0.9761Buffered data was truncated after reaching the output si
     ze limit.
In [0]: import matplotlib.pyplot as plt
     scores = model.evaluate(testarray1, testy, verbose=0)
     print("Accuracy: %.2f%" % (scores[1]*100))
     # Test and train accuracy of the model
     model 3 test = scores[1]
```

```
model_3_train = max(history.history['acc'])

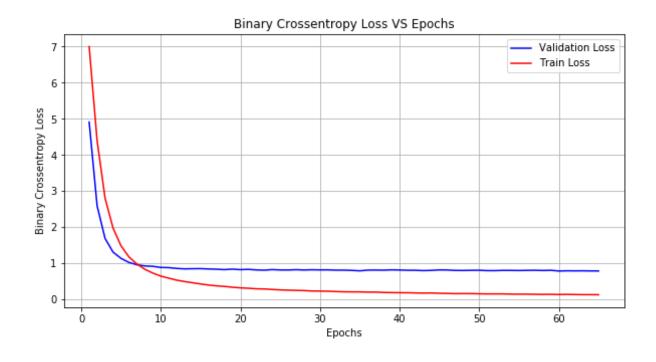
# Plotting Train and Test Loss VS no. of epochs
# list of epoch numbers
x = list(range(1,66))

# Validation loss

vy = history.history['val_loss']
# Training loss
ty = history.history['loss']

# Calling the function to draw the plot
plt_dynamic(x, vy, ty)
```

Accuracy: 88.89%



In [0]: import keras as keras

```
import tensorflow as tf
from keras.models import Sequential
from keras.layers import Dense,Dropout,Flatten,BatchNormalization
from keras.layers import Conv1D,MaxPooling1D
model=Sequential()
model.add(Conv1D(100,kernel size=(26),activation='relu',input shape=(20)
0,26)))
model.add(MaxPooling1D(pool size=2))
model.add(Dropout(0.5))
model.add(Conv1D(250,26,activation='relu'))
model.add(MaxPooling1D(pool size=4))
model.add(Flatten())
model.add(Dense(11180,activation='softmax'))
model.compile(loss=keras.losses.sparse categorical crossentropy,optimiz
er='adam',metrics=['accuracy'])
history=model.fit(trainarray1,trainy,epochs=60,validation data=[testarr
av1, testyl, batch size=128)
W0618 17:02:57.990099 140483376052096 nn ops.py:4224] Large dropout rat
e: 0.6 (>0.5). In TensorFlow 2.x, dropout() uses dropout rate instead o
f keep prob. Please ensure that this is intended.
Train on 130000 samples, validate on 20000 samples
Epoch 1/60
6.9390 - acc: 0.0836 - val loss: 4.6362 - val acc: 0.3158
Epoch 2/60
4.3252 - acc: 0.3231 - val loss: 2.6183 - val acc: 0.5752
Epoch 3/60
2.9310 - acc: 0.4804 - val loss: 1.8188 - val acc: 0.6942
Epoch 4/60
2.1949 - acc: 0.5759 - val loss: 1.4445 - val acc: 0.7467
Epoch 5/60
1.7564 - acc: 0.6377 - val loss: 1.2535 - val acc: 0.7788
Epoch 6/60
```

```
1.4390 - acc: 0.6879 - val loss: 1.1255 - val acc: 0.8014
Epoch 7/60
1.2149 - acc: 0.7254 - val loss: 1.0493 - val acc: 0.8143
Epoch 8/60
1.0434 - acc: 0.7577 - val loss: 0.9952 - val acc: 0.8243
Epoch 9/60
0.9207 - acc: 0.7793 - val loss: 0.9584 - val acc: 0.8323
Epoch 10/60
0.8185 - acc: 0.7998 - val loss: 0.9210 - val acc: 0.8423
Epoch 11/60
0.7371 - acc: 0.8177 - val loss: 0.8977 - val acc: 0.8477
Epoch 12/60
0.6679 - acc: 0.8312 - val loss: 0.8848 - val acc: 0.8504
Epoch 13/60
0.6205 - acc: 0.8411 - val loss: 0.8671 - val acc: 0.8534
Epoch 14/60
0.5728 - acc: 0.8515 - val loss: 0.8536 - val acc: 0.8585
Epoch 15/60
0.5408 - acc: 0.8592 - val loss: 0.8465 - val acc: 0.8614
Epoch 16/60
0.5023 - acc: 0.8678 - val loss: 0.8340 - val acc: 0.8633
Epoch 17/60
0.4788 - acc: 0.8731 - val loss: 0.8375 - val acc: 0.8637
Epoch 18/60
0.4502 - acc: 0.8786 - val loss: 0.8299 - val acc: 0.8683
Epoch 19/60
```

```
0.4278 - acc: 0.8847 - val loss: 0.8158 - val acc: 0.8703
Epoch 20/60
0.4183 - acc: 0.8872 - val loss: 0.8119 - val acc: 0.8694
Epoch 21/60
0.3872 - acc: 0.8940 - val loss: 0.8085 - val acc: 0.8741
Epoch 22/60
0.3785 - acc: 0.8960 - val loss: 0.8044 - val acc: 0.8760
Epoch 23/60
0.3663 - acc: 0.9000 - val_loss: 0.7931 - val acc: 0.8763
Epoch 24/60
0.3512 - acc: 0.9044 - val loss: 0.7933 - val acc: 0.8755
Epoch 25/60
0.3425 - acc: 0.9045 - val loss: 0.7896 - val acc: 0.8770
Epoch 26/60
0.3285 - acc: 0.9098 - val loss: 0.7876 - val acc: 0.8783
Epoch 27/60
0.3170 - acc: 0.9116 - val loss: 0.7894 - val acc: 0.8776
Epoch 28/60
0.3065 - acc: 0.9144 - val loss: 0.7886 - val acc: 0.8787
Epoch 29/60
0.3018 - acc: 0.9168 - val loss: 0.7785 - val acc: 0.8802
Epoch 30/60
0.2937 - acc: 0.9188 - val loss: 0.7768 - val acc: 0.8818
Epoch 31/60
0.2796 - acc: 0.9221 - val loss: 0.7875 - val acc: 0.8797
Epoch 32/60
```

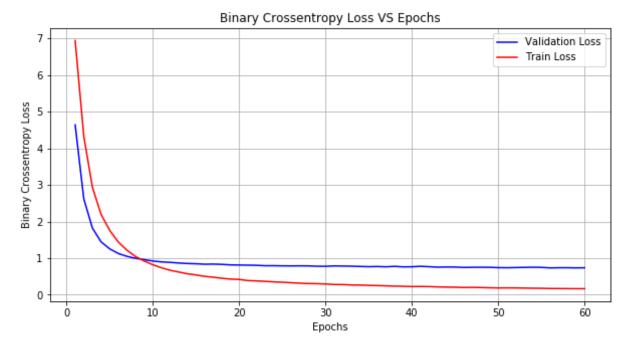
```
0.2782 - acc: 0.9229 - val loss: 0.7841 - val acc: 0.8820
Epoch 33/60
0.2666 - acc: 0.9250 - val loss: 0.7796 - val acc: 0.8818
Epoch 34/60
0.2644 - acc: 0.9255 - val loss: 0.7733 - val acc: 0.8841
Epoch 35/60
0.2563 - acc: 0.9283 - val loss: 0.7663 - val acc: 0.8838
Epoch 36/60
0.2503 - acc: 0.9292 - val loss: 0.7710 - val acc: 0.8845
Epoch 37/60
0.2434 - acc: 0.9309 - val loss: 0.7629 - val acc: 0.8854
Epoch 38/60
0.2353 - acc: 0.9340 - val loss: 0.7754 - val acc: 0.8861
Epoch 39/60
0.2319 - acc: 0.9354 - val loss: 0.7614 - val acc: 0.8864
Epoch 40/60
0.2229 - acc: 0.9369 - val loss: 0.7643 - val acc: 0.8881
Epoch 41/60
0.2258 - acc: 0.9369 - val loss: 0.7774 - val acc: 0.8855
Epoch 42/60
0.2225 - acc: 0.9371 - val loss: 0.7653 - val acc: 0.8879
Epoch 43/60
0.2145 - acc: 0.9405 - val loss: 0.7537 - val acc: 0.8883
Epoch 44/60
0.2090 - acc: 0.9409 - val loss: 0.7583 - val acc: 0.8892
Epoch 45/60
```

```
0.2064 - acc: 0.9416 - val loss: 0.7566 - val acc: 0.8908
Epoch 46/60
0.1980 - acc: 0.9438 - val loss: 0.7459 - val acc: 0.8921
Epoch 47/60
0.2013 - acc: 0.9433 - val loss: 0.7500 - val acc: 0.8924
Epoch 48/60
0.1967 - acc: 0.9440 - val loss: 0.7514 - val acc: 0.8904
Epoch 49/60
0.1909 - acc: 0.9455 - val loss: 0.7493 - val acc: 0.8915
Epoch 50/60
0.1859 - acc: 0.9466 - val loss: 0.7406 - val acc: 0.8928
Epoch 51/60
0.1883 - acc: 0.9466 - val loss: 0.7377 - val acc: 0.8928
Epoch 52/60
0.1864 - acc: 0.9478 - val loss: 0.7423 - val acc: 0.8935
Epoch 53/60
0.1824 - acc: 0.9482 - val loss: 0.7467 - val acc: 0.8924
Epoch 54/60
0.1782 - acc: 0.9497 - val loss: 0.7514 - val acc: 0.8924
Epoch 55/60
0.1761 - acc: 0.9503 - val loss: 0.7476 - val acc: 0.8924
Epoch 56/60
0.1707 - acc: 0.9520 - val loss: 0.7331 - val acc: 0.8934
Epoch 57/60
0.1691 - acc: 0.9516 - val loss: 0.7376 - val acc: 0.8932
Epoch 58/60
```

```
0.1672 - acc: 0.9517 - val_loss: 0.7382 - val_acc: 0.8957
Epoch 59/60
130000/130000 [=============] - 60s 462us/step - loss:
0.1652 - acc: 0.9532 - val_loss: 0.7340 - val_acc: 0.8971
Epoch 60/60
130000/130000 [=============] - 60s 462us/step - loss:
0.1650 - acc: 0.9524 - val_loss: 0.7369 - val_acc: 0.8960
In [0]: import matplotlib.pyplot as plt
scores = model.evaluate(testarray1, testy, verbose=0)
print("Accuracy: %.2f%%" % (scores[1]*100))

# Test and train accuracy of the model
model_3_test = scores[1]
# Calling the function to draw the plot
plt_dynamic(x, vy, ty)

Accuracy: 89.60%
```



```
In [0]: import keras as keras
        import tensorflow as tf
        from keras.models import Sequential
        from keras.layers import Dense,Dropout,Flatten,BatchNormalization
        from keras.layers import Conv1D, MaxPooling1D
        model=Sequential()
        model.add(Conv1D(1500, kernel size=21, activation='relu', input shape=(200
        ,26)))
        model.add(MaxPooling1D(pool size=2))
        model.add(Dropout(0.5))
        model.add(BatchNormalization())
        model.add(Conv1D(500,26,dilation rate=2,activation='relu'))
        model.add(MaxPooling1D(pool size=4))
        model.add(Dropout(0.4))
        model.add(BatchNormalization())
        model.add(Conv1D(512,1,activation='relu'))
        model.add(MaxPooling1D(pool size=4))
        model.add(Dropout(0.4))
```

```
model.add(BatchNormalization())
model.add(Flatten())
model.add(Dense(11180,activation='softmax'))
model.compile(loss=keras.losses.sparse categorical crossentropy,optimiz
er='adam', metrics=['accuracy'])
history=model.fit(trainarray1, trainy, epochs=100, validation data=[testar
ray1, testy], batch size=256)
Train on 130000 samples, validate on 20000 samples
Epoch 1/100
6.5850 - acc: 0.1133 - val loss: 4.0728 - val acc: 0.3664
Epoch 2/100
3.2637 - acc: 0.4496 - val loss: 2.0201 - val acc: 0.6458
Epoch 3/100
1.7078 - acc: 0.6577 - val loss: 1.3805 - val acc: 0.7435
Epoch 4/100
1.0127 - acc: 0.7693 - val loss: 1.0908 - val acc: 0.7903
Epoch 5/100
0.6610 - acc: 0.8369 - val loss: 0.9763 - val acc: 0.8131
Epoch 6/100
0.4879 - acc: 0.8733 - val loss: 0.9408 - val acc: 0.8196
Epoch 7/100
0.3828 - acc: 0.8969 - val loss: 0.8822 - val acc: 0.8310
Epoch 8/100
0.3162 - acc: 0.9114 - val loss: 0.8725 - val acc: 0.8351
Epoch 9/100
0.2695 - acc: 0.9239 - val loss: 0.8530 - val acc: 0.8440
Epoch 10/100
0.2446 - acc: 0.9300 - val loss: 0.8557 - val acc: 0.8419
Epoch 11/100
```

```
0.2211 - acc: 0.9363 - val loss: 0.8405 - val acc: 0.8483
Epoch 12/100
0.1988 - acc: 0.9425 - val loss: 0.8408 - val acc: 0.8520
Epoch 13/100
0.1876 - acc: 0.9452 - val loss: 0.8326 - val acc: 0.8523
Epoch 14/100
0.1750 - acc: 0.9496 - val loss: 0.8308 - val acc: 0.8574
Epoch 15/100
0.1687 - acc: 0.9505 - val loss: 0.8251 - val acc: 0.8560
Epoch 16/100
0.1543 - acc: 0.9547 - val loss: 0.8130 - val acc: 0.8601
Epoch 17/100
0.1448 - acc: 0.9578 - val loss: 0.8132 - val acc: 0.8623
Epoch 18/100
0.1392 - acc: 0.9587 - val loss: 0.8004 - val acc: 0.8649
Epoch 19/100
0.1340 - acc: 0.9605 - val loss: 0.8170 - val acc: 0.8648
Epoch 20/100
0.1300 - acc: 0.9628 - val loss: 0.8300 - val acc: 0.8640
Epoch 21/100
0.1245 - acc: 0.9630 - val loss: 0.8126 - val acc: 0.8669
Epoch 22/100
0.1153 - acc: 0.9661 - val loss: 0.8035 - val acc: 0.8697
Epoch 23/100
0.1156 - acc: 0.9666 - val loss: 0.8372 - val acc: 0.8675
Epoch 24/100
```

```
0.1095 - acc: 0.9674 - val loss: 0.8409 - val acc: 0.8671
Epoch 25/100
0.1080 - acc: 0.9684 - val loss: 0.8288 - val acc: 0.8711
Epoch 26/100
0.1034 - acc: 0.9698 - val loss: 0.8144 - val acc: 0.8722
Epoch 27/100
0.0979 - acc: 0.9713 - val loss: 0.8275 - val acc: 0.8722
Epoch 28/100
0.0979 - acc: 0.9712 - val loss: 0.8265 - val acc: 0.8711
Epoch 29/100
0.0949 - acc: 0.9720 - val loss: 0.8239 - val acc: 0.8712
Epoch 30/100
0.0903 - acc: 0.9736 - val loss: 0.8343 - val acc: 0.8719
Epoch 31/100
0.0860 - acc: 0.9751 - val loss: 0.8114 - val acc: 0.8744
Epoch 32/100
0.0844 - acc: 0.9750 - val loss: 0.8240 - val acc: 0.8759
Epoch 33/100
0.0809 - acc: 0.9760 - val loss: 0.8141 - val acc: 0.8765
Epoch 34/100
0.0840 - acc: 0.9752 - val loss: 0.8193 - val acc: 0.8747
Epoch 35/100
0.0784 - acc: 0.9772 - val loss: 0.8078 - val acc: 0.8781
Epoch 36/100
0.0772 - acc: 0.9774 - val loss: 0.8039 - val acc: 0.8791
Epoch 37/100
```

```
0.0778 - acc: 0.9775 - val loss: 0.8066 - val acc: 0.8803
Epoch 38/100
0.0749 - acc: 0.9784 - val loss: 0.8236 - val acc: 0.8801
Epoch 39/100
0.0733 - acc: 0.9788 - val loss: 0.8207 - val acc: 0.8794
Epoch 40/100
0.0713 - acc: 0.9795 - val loss: 0.8178 - val acc: 0.8803
Epoch 41/100
0.0689 - acc: 0.9799 - val loss: 0.8259 - val acc: 0.8796
Epoch 42/100
0.0686 - acc: 0.9804 - val loss: 0.8047 - val acc: 0.8827
Epoch 43/100
0.0682 - acc: 0.9804 - val loss: 0.8131 - val acc: 0.8815
Epoch 44/100
0.0675 - acc: 0.9807 - val loss: 0.8176 - val acc: 0.8826
Epoch 45/100
0.0646 - acc: 0.9813 - val loss: 0.8021 - val acc: 0.8826
Epoch 46/100
0.0627 - acc: 0.9823 - val loss: 0.8121 - val acc: 0.8821
Epoch 47/100
0.0601 - acc: 0.9827 - val loss: 0.8150 - val acc: 0.8822
Epoch 48/100
0.0602 - acc: 0.9829 - val loss: 0.8108 - val acc: 0.8814
Epoch 49/100
0.0581 - acc: 0.9834 - val loss: 0.8134 - val acc: 0.8820
Epoch 50/100
```

```
0.0590 - acc: 0.9832 - val loss: 0.8152 - val acc: 0.8842
Epoch 51/100
0.0582 - acc: 0.9834 - val loss: 0.8135 - val acc: 0.8838
Epoch 52/100
0.0567 - acc: 0.9838 - val loss: 0.8171 - val acc: 0.8846
Epoch 53/100
0.0579 - acc: 0.9838 - val loss: 0.8127 - val acc: 0.8850
Epoch 54/100
0.0541 - acc: 0.9842 - val loss: 0.8073 - val acc: 0.8851
Epoch 55/100
0.0535 - acc: 0.9848 - val loss: 0.8122 - val acc: 0.8840
Epoch 56/100
0.0555 - acc: 0.9847 - val loss: 0.8182 - val acc: 0.8858
Epoch 57/100
0.0531 - acc: 0.9853 - val loss: 0.8082 - val acc: 0.8859
Epoch 58/100
0.0511 - acc: 0.9857 - val loss: 0.7998 - val acc: 0.8863
Epoch 59/100
0.0519 - acc: 0.9857 - val loss: 0.8064 - val acc: 0.8867
Epoch 60/100
0.0509 - acc: 0.9856 - val loss: 0.8140 - val acc: 0.8846
Epoch 61/100
0.0504 - acc: 0.9858 - val loss: 0.8104 - val acc: 0.8834
Epoch 62/100
0.0497 - acc: 0.9860 - val loss: 0.8116 - val acc: 0.8868
Epoch 63/100
```

```
0.0493 - acc: 0.9858 - val loss: 0.8004 - val acc: 0.8871
Epoch 64/100
0.0480 - acc: 0.9864 - val loss: 0.8082 - val acc: 0.8874
Epoch 65/100
0.0437 - acc: 0.9876 - val loss: 0.8151 - val acc: 0.8877
Epoch 66/100
0.0470 - acc: 0.9866 - val loss: 0.7966 - val acc: 0.8879
Epoch 67/100
0.0453 - acc: 0.9872 - val loss: 0.8057 - val acc: 0.8887
Epoch 68/100
0.0452 - acc: 0.9874 - val loss: 0.8074 - val acc: 0.8878
Epoch 69/100
0.0447 - acc: 0.9875 - val loss: 0.8000 - val acc: 0.8892
Epoch 70/100
0.0426 - acc: 0.9882 - val loss: 0.8054 - val acc: 0.8882
Epoch 71/100
0.0437 - acc: 0.9878 - val loss: 0.7996 - val acc: 0.8881
Epoch 72/100
0.0422 - acc: 0.9882 - val loss: 0.8031 - val acc: 0.8898
Epoch 73/100
0.0425 - acc: 0.9882 - val loss: 0.8017 - val acc: 0.8912
Epoch 74/100
0.0417 - acc: 0.9884 - val loss: 0.8013 - val acc: 0.8901
Epoch 75/100
0.0427 - acc: 0.9880 - val loss: 0.8003 - val acc: 0.8920
Epoch 76/100
```

```
0.0430 - acc: 0.9882 - val loss: 0.8002 - val acc: 0.8924
Epoch 77/100
0.0407 - acc: 0.9888 - val loss: 0.7862 - val acc: 0.8913
Epoch 78/100
0.0396 - acc: 0.9888 - val loss: 0.7895 - val acc: 0.8913
Epoch 79/100
0.0397 - acc: 0.9890 - val loss: 0.7963 - val acc: 0.8908
Epoch 80/100
0.0386 - acc: 0.9894 - val loss: 0.7989 - val acc: 0.8905
Epoch 81/100
0.0381 - acc: 0.9892 - val loss: 0.8054 - val acc: 0.8910
Epoch 82/100
0.0393 - acc: 0.9891 - val loss: 0.7988 - val acc: 0.8911
Epoch 83/100
0.0383 - acc: 0.9895 - val loss: 0.7946 - val acc: 0.8934
Epoch 84/100
0.0360 - acc: 0.9898 - val loss: 0.8105 - val acc: 0.8912
Epoch 85/100
0.0359 - acc: 0.9901 - val loss: 0.7996 - val acc: 0.8938
Epoch 86/100
0.0374 - acc: 0.9895 - val loss: 0.7912 - val acc: 0.8924
Epoch 87/100
0.0360 - acc: 0.9902 - val loss: 0.7915 - val acc: 0.8948
Epoch 88/100
0.0361 - acc: 0.9898 - val loss: 0.7991 - val acc: 0.8948
Epoch 89/100
```

```
0.0377 - acc: 0.9894 - val loss: 0.7881 - val acc: 0.8951
    Epoch 90/100
    0.0354 - acc: 0.9904 - val loss: 0.7907 - val acc: 0.8933
    Epoch 91/100
    0.0365 - acc: 0.9904 - val loss: 0.7820 - val acc: 0.8940
    Epoch 92/100
    0.0348 - acc: 0.9903 - val loss: 0.7792 - val acc: 0.8920
    Epoch 93/100
    0.0329 - acc: 0.9908 - val loss: 0.7893 - val acc: 0.8932
    Epoch 94/100
    0.0346 - acc: 0.9905 - val loss: 0.7954 - val acc: 0.8935
    Epoch 95/100
    0.0333 - acc: 0.9909 - val loss: 0.7850 - val acc: 0.8938
    Epoch 96/100
    0.0326 - acc: 0.9914 - val loss: 0.7812 - val acc: 0.8950
    Epoch 97/100
    0.0331 - acc: 0.9909 - val loss: 0.7753 - val acc: 0.8949
    Epoch 98/100
    0.0327 - acc: 0.9910 - val loss: 0.7795 - val acc: 0.8951
    Epoch 99/100
    0.0311 - acc: 0.9914 - val loss: 0.7846 - val acc: 0.8947
    Epoch 100/100
    0.0312 - acc: 0.9918 - val loss: 0.7741 - val acc: 0.8962
In [0]: import keras as keras
    import tensorflow as tf
    from keras.models import Sequential
```

```
from keras.layers import Dense,Dropout,Flatten,BatchNormalization
from keras.layers import Conv1D, MaxPooling1D
from keras.layers import LSTM, Bidirectional
model=Sequential()
model.add(Conv1D(500,kernel size=(26),activation='relu',input shape=(20)
0,26)))
model.add(MaxPooling1D(pool size=2))
model.add(Dropout(0.5))
model.add(Conv1D(250,26,activation='relu'))
model.add(MaxPooling1D(pool size=4))
model.add(Dropout(0.7))
model.add(Bidirectional(LSTM(300,dropout=0.4,return sequences=True)))
model.add(Flatten())
model.add(Dense(11180.activation='softmax'))
model.compile(loss=keras.losses.sparse categorical crossentropy,optimiz
er='adam',metrics=['accuracy'])
history=model.fit(trainarray1,trainy,epochs=60,validation data=[testarr
av1, testy], batch size=128)
WARNING: Logging before flag parsing goes to stderr.
W0619 07:20:06.596103 140182523484032 deprecation wrapper.py:119] From
/usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow backen
d.py:74: The name tf.get default graph is deprecated. Please use tf.com
pat.v1.get_default graph instead.
W0619 07:20:06.654401 140182523484032 deprecation wrapper.py:119] From
/usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow backen
d.pv:517: The name tf.placeholder is deprecated. Please use tf.compat.v
1.placeholder instead.
W0619 07:20:06.676386 140182523484032 deprecation wrapper.py:119] From
/usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow backen
d.py:4138: The name tf.random uniform is deprecated. Please use tf.rand
om.uniform instead.
W0619 07:20:06.721345 140182523484032 deprecation wrapper.py:119] From
/usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow backen
d.py:3976: The name tf.nn.max pool is deprecated. Please use tf.nn.max
pool2d instead.
```

W0619 07:20:06.729445 140182523484032 deprecation wrapper.py:119] From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow backen d.py:133: The name tf.placeholder with default is deprecated. Please us e tf.compat.v1.placeholder with default instead. W0619 07:20:06.741749 140182523484032 deprecation.py:5061 From /usr/loc al/lib/python3.6/dist-packages/keras/backend/tensorflow backend.py:344 5: calling dropout (from tensorflow.python.ops.nn ops) with keep prob i s deprecated and will be removed in a future version. Instructions for updating: Please use `rate` instead of `keep prob`. Rate should be set to `rate = 1 - keep prob`. W0619 07:20:06.790762 140182523484032 nn ops.py:4224] Large dropout rat e: 0.7 (>0.5). In TensorFlow 2.x, dropout() uses dropout rate instead o f keep prob. Please ensure that this is intended. W0619 07:20:07.862491 140182523484032 deprecation wrapper.py:119] From /usr/local/lib/python3.6/dist-packages/keras/optimizers.py:790: The nam e tf.train.Optimizer is deprecated. Please use tf.compat.v1.train.Optim izer instead. W0619 07:20:07.891538 140182523484032 deprecation wrapper.py:119] From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow backen d.py:3341: The name tf.log is deprecated. Please use tf.math.log instea d. W0619 07:20:08.062929 140182523484032 deprecation.pv:3231 From /usr/loc al/lib/python3.6/dist-packages/tensorflow/python/ops/math grad.py:1250: add dispatch support.<locals>.wrapper (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 Train on 130000 samples, validate on 20000 samples Epoch 1/60 6.2155 - acc: 0.1286 - val loss: 3.5157 - val acc: 0.3762

```
Epoch 1/60
130000/130000 [===========] - 349s 3ms/step - loss:
6.2155 - acc: 0.1286 - val_loss: 3.5157 - val_acc: 0.3762
Epoch 2/60
130000/130000 [=============] - 340s 3ms/step - loss:
3.0838 - acc: 0.4326 - val_loss: 1.9675 - val_acc: 0.6191
Epoch 3/60
```

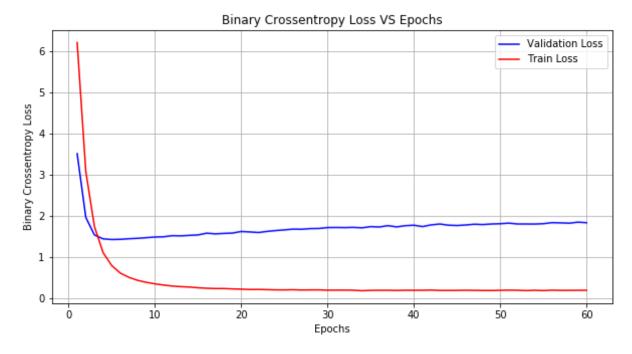
```
1.7447 - acc: 0.6145 - val loss: 1.5395 - val acc: 0.7067
Epoch 4/60
1.1114 - acc: 0.7286 - val loss: 1.4451 - val acc: 0.7418
Epoch 5/60
0.7962 - acc: 0.7921 - val loss: 1.4290 - val acc: 0.7565
Epoch 6/60
0.6128 - acc: 0.8333 - val loss: 1.4331 - val acc: 0.7676
Epoch 7/60
0.5084 - acc: 0.8577 - val loss: 1.4481 - val acc: 0.7764
Epoch 8/60
0.4364 - acc: 0.8759 - val loss: 1.4578 - val acc: 0.7810
Epoch 9/60
0.3888 - acc: 0.8885 - val loss: 1.4733 - val acc: 0.7853
Epoch 10/60
0.3509 - acc: 0.8988 - val loss: 1.4891 - val acc: 0.7907
Epoch 11/60
0.3227 - acc: 0.9067 - val loss: 1.4949 - val acc: 0.7913
Epoch 12/60
0.2980 - acc: 0.9138 - val loss: 1.5222 - val acc: 0.7931
Epoch 13/60
0.2831 - acc: 0.9173 - val loss: 1.5176 - val acc: 0.7964
Epoch 14/60
0.2732 - acc: 0.9201 - val loss: 1.5296 - val acc: 0.7997
Epoch 15/60
0.2556 - acc: 0.9246 - val loss: 1.5402 - val acc: 0.7997
Epoch 16/60
```

```
0.2444 - acc: 0.9286 - val loss: 1.5830 - val acc: 0.8005
Epoch 17/60
0.2366 - acc: 0.9312 - val loss: 1.5664 - val_acc: 0.8042
Epoch 18/60
0.2372 - acc: 0.9312 - val loss: 1.5775 - val acc: 0.8046
Epoch 19/60
0.2278 - acc: 0.9343 - val loss: 1.5857 - val acc: 0.8061
Epoch 20/60
0.2228 - acc: 0.9357 - val loss: 1.6240 - val acc: 0.8030
Epoch 21/60
0.2140 - acc: 0.9391 - val loss: 1.6130 - val acc: 0.8078
Epoch 22/60
0.2165 - acc: 0.9390 - val loss: 1.5987 - val acc: 0.8099
Epoch 23/60
0.2104 - acc: 0.9390 - val loss: 1.6263 - val_acc: 0.8075
Epoch 24/60
0.2052 - acc: 0.9418 - val loss: 1.6465 - val acc: 0.8088
Epoch 25/60
0.2041 - acc: 0.9415 - val loss: 1.6627 - val acc: 0.8090
Epoch 26/60
0.2080 - acc: 0.9418 - val loss: 1.6815 - val acc: 0.8046
Epoch 27/60
0.2014 - acc: 0.9441 - val loss: 1.6783 - val acc: 0.8095
Epoch 28/60
0.2040 - acc: 0.9430 - val loss: 1.6943 - val acc: 0.8099
Epoch 29/60
```

```
0.2047 - acc: 0.9438 - val loss: 1.6972 - val acc: 0.8105
Epoch 30/60
0.1971 - acc: 0.9450 - val loss: 1.7195 - val acc: 0.8112
Epoch 31/60
0.1986 - acc: 0.9454 - val loss: 1.7212 - val acc: 0.8119
Epoch 32/60
0.1990 - acc: 0.9453 - val loss: 1.7186 - val acc: 0.8127
Epoch 33/60
0.1960 - acc: 0.9467 - val loss: 1.7237 - val acc: 0.8124
Epoch 34/60
0.1843 - acc: 0.9495 - val loss: 1.7130 - val acc: 0.8155
Epoch 35/60
0.1923 - acc: 0.9481 - val loss: 1.7422 - val acc: 0.8147
Epoch 36/60
0.1946 - acc: 0.9480 - val loss: 1.7336 - val_acc: 0.8167
Epoch 37/60
0.1947 - acc: 0.9477 - val loss: 1.7657 - val acc: 0.8124
Epoch 38/60
0.1906 - acc: 0.9494 - val loss: 1.7356 - val acc: 0.8168
Epoch 39/60
0.1955 - acc: 0.9485 - val loss: 1.7648 - val acc: 0.8152
Epoch 40/60
0.1948 - acc: 0.9490 - val loss: 1.7760 - val acc: 0.8155
Epoch 41/60
0.1953 - acc: 0.9485 - val loss: 1.7433 - val acc: 0.8191
Epoch 42/60
```

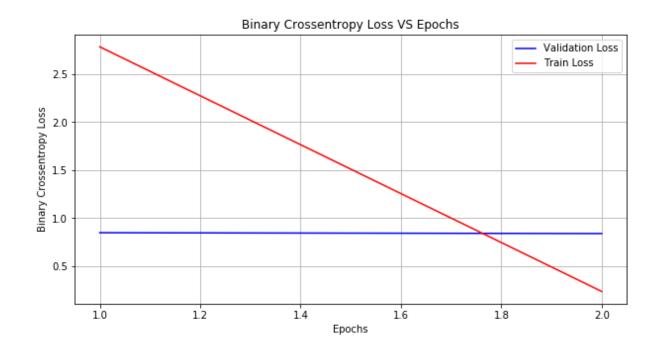
```
0.2005 - acc: 0.9478 - val loss: 1.7837 - val acc: 0.8141
Epoch 43/60
0.1910 - acc: 0.9501 - val loss: 1.8055 - val_acc: 0.8152
Epoch 44/60
0.1905 - acc: 0.9499 - val loss: 1.7772 - val acc: 0.8165
Epoch 45/60
0.1924 - acc: 0.9496 - val loss: 1.7689 - val acc: 0.8193
Epoch 46/60
0.1957 - acc: 0.9501 - val loss: 1.7821 - val acc: 0.8154
Epoch 47/60
0.1924 - acc: 0.9503 - val loss: 1.7999 - val acc: 0.8162
Epoch 48/60
0.1900 - acc: 0.9513 - val loss: 1.7920 - val acc: 0.8177
Epoch 49/60
0.1890 - acc: 0.9515 - val loss: 1.8059 - val acc: 0.8164
Epoch 50/60
0.1940 - acc: 0.9506 - val loss: 1.8129 - val acc: 0.8175
Epoch 51/60
0.1983 - acc: 0.9498 - val loss: 1.8269 - val acc: 0.8174
Epoch 52/60
0.1956 - acc: 0.9512 - val loss: 1.8062 - val acc: 0.8207
Epoch 53/60
0.1870 - acc: 0.9521 - val loss: 1.8060 - val acc: 0.8187
Epoch 54/60
0.1947 - acc: 0.9513 - val loss: 1.8046 - val acc: 0.8191
Epoch 55/60
```

```
0.1873 - acc: 0.9536 - val loss: 1.8131 - val acc: 0.8185
       Epoch 56/60
       0.1971 - acc: 0.9510 - val loss: 1.8387 - val acc: 0.8175
       Epoch 57/60
       0.1924 - acc: 0.9525 - val loss: 1.8332 - val acc: 0.8174
       Epoch 58/60
       28800/130000 [=====>.....] - ETA: 4:17 - loss: 0.17
       89 - acc: 0.9552Buffered data was truncated after reaching the output s
       ize limit.
In [0]: import matplotlib.pyplot as plt
       scores = model.evaluate(testarray1, testy, verbose=0)
       print("Accuracy: %.2f%" % (scores[1]*100))
       # Test and train accuracy of the model
       model 3 test = scores[1]
       model 3 train = max(history.history['acc'])
       # Plotting Train and Test Loss VS no. of epochs
       # list of epoch numbers
       x = list(range(1,61))
       # Validation loss
       vy = history.history['val loss']
       # Training loss
       ty = history.history['loss']
       # Calling the function to draw the plot
       plt dynamic(x, vy, ty)
       Accuracy: 81.77%
```



```
In [0]: import keras as keras
        import tensorflow as tf
        from keras.models import Sequential
        from keras.layers import Dense,Dropout,Flatten,BatchNormalization
        from keras.layers import Conv1D, MaxPooling1D
        from keras.layers import LSTM, Bidirectional
        model=Sequential()
        model.add(Dense(200,activation='relu',input shape=(200,26)))
        model.add(Dropout(0.4))
        model.add(BatchNormalization())
        model.add(Bidirectional(LSTM(26,dropout=0.2,return sequences=True)))
        model.add(BatchNormalization())
        model.add(Flatten())
        model.add(Dense(11180,activation='softmax'))
        model.compile(loss=keras.losses.sparse categorical crossentropy,optimiz
        er='adam', metrics=['accuracy'])
        history=model.fit(trainarray1, trainy, epochs=2, validation data=[testarra
        y1, testy], batch size=128)
```

```
Train on 130000 samples, validate on 20000 samples
       Epoch 1/2
       2.7829 - acc: 0.6851 - val loss: 0.8493 - val acc: 0.8886
       Epoch 2/2
       0.2382 - acc: 0.9801 - val loss: 0.8404 - val acc: 0.8921
In [0]: import matplotlib.pyplot as plt
       scores = model.evaluate(testarray1, testy, verbose=0)
       print("Accuracy: %.2f%" % (scores[1]*100))
       # Test and train accuracy of the model
       model 3 test = scores[1]
       model 3 train = max(history.history['acc'])
       # Plotting Train and Test Loss VS no. of epochs
       # list of epoch numbers
       x = list(range(1,3))
       # Validation loss
       vy = history.history['val loss']
       # Training loss
       ty = history.history['loss']
       # Calling the function to draw the plot
       plt dynamic(x, vy, ty)
       Accuracy: 89.22%
```



** WITH 180000 POINTS AS TRIAINING DATA

```
In [0]: import pandas as pd
import numpy as np

In [0]: !pip install -U -q PyDrive
    from pydrive.auth import GoogleAuth
    from pydrive.drive import GoogleDrive
    from google.colab import auth
    from oauth2client.client import GoogleCredentials
    # Authenticate and create the PyDrive client.
    auth.authenticate_user()
    gauth = GoogleAuth()
```

```
gauth.credentials = GoogleCredentials.get application default()
        drive = GoogleDrive(gauth)
                                                993kB 6.6MB/s
          Building wheel for PyDrive (setup.py) ... done
In [0]: link = 'https://drive.google.com/open?id=1dRP2sKGX 8o0qlRSR2FQNUhneR3bf
        Grc' # The shareable link
In [0]: fluff, id = link.split('=')
In [0]: import pickle
        downloaded = drive.CreateFile({'id':id})
        downloaded.GetContentFile('trainarray.npy')
        trainarray= np.load('trainarray.npy')
In [0]: link = 'https://drive.google.com/open?id=1Bd2MrmGsDVm0Zqt5xCphyhLWHctu0
        wG8' # The shareable link
In [0]: fluff, id = link.split('=')
In [0]: downloaded = drive.CreateFile({'id':id})
        downloaded.GetContentFile('testarray.npy')
        testarray= np.load('testarray.npy')
In [0]: link = 'https://drive.google.com/open?id=1Di8VvI-XxNcTtcYIC3zk-l001Ti0P
        UOq' # The shareable link
In [0]: fluff, id = link.split('=')
In [0]: downloaded = drive.CreateFile({'id':id})
        downloaded.GetContentFile('cvarray.npy')
        cvarray= np.load('cvarray.npy')
In [0]: link = 'https://drive.google.com/open?id=1Jw6cyVYaJ-HL160x6X0Ab5KsqQxGE
```

```
ClR' # The shareable link
In [0]: fluff, id = link.split('=')
In [0]: downloaded = drive.CreateFile({'id':id})
        downloaded.GetContentFile('traindataframeclasslabel.csv')
        traindataframe= pd.read csv('traindataframeclasslabel.csv',names=['a',
        'b'1)
In [0]: link = 'https://drive.google.com/open?id=1hhWTqUSQ1TVQtvp-YN36E5sCx7XkP
        Dh7' # The shareable link
In [0]: fluff, id = link.split('=')
In [0]: downloaded = drive.CreateFile({'id':id})
        downloaded.GetContentFile('testdataframeclasslabel.csv')
        testdataframe= pd.read csv('testdataframeclasslabel.csv',names=['a','b'
        1)
In [0]: link = 'https://drive.google.com/open?id=1BzVl-SWjGkQ1819BSQ9GbgHf-8PLc
        JNH' # The shareable link
In [0]: fluff, id = link.split('=')
In [0]: downloaded = drive.CreateFile({'id':id})
        downloaded.GetContentFile('cvdataframeclasslabel.csv')
        cvdataframe= pd.read csv('cvdataframeclasslabel.csv',names=['a','b'])
In [0]: print(traindataframe.shape)
        print(testdataframe.shape)
        print(cvdataframe.shape)
        (180000,)
        (20000, 2)
        (20000, 2)
```

```
In [0]: print(traindataframe.head(3))
        0
              PF13376.6
        1
             PF01381.22
             PF00300.22
        Name: b, dtype: object
In [0]: traindataframe=traindataframe['b']
In [0]: testdataframe=testdataframe['b']
        cvdataframe=cvdataframe['b']
In [0]: totaldataframe=pd.concat([traindataframe, testdataframe],axis=0)
In [0]: totaldataframe.head(3)
Out[0]: 0
              PF13376.6
             PF01381.22
             PF00300.22
        Name: b, dtype: object
In [0]: from sklearn.feature extraction.text import CountVectorizer
        vect=CountVectorizer()
        out=vect.fit transform(totaldataframe)
        features=vect.get feature names()
        counts=out.sum(axis=0)
        print('number of unique class lables are',len(features))
        number of unique class lables are 11836
In [0]: from keras.models import Sequential
        from keras.layers import Flatten, Activation, Dense, Dropout
        from keras.utils import np utils
In [0]: from sklearn.preprocessing import LabelEncoder
        label1=LabelEncoder()
```

```
label1.fit(totaldataframe)
        trainy=label1.transform(traindataframe)
        testy=label1.transform(testdataframe)
        #cvy=label1.transform(cvdataframe['family accession'])
In [0]: # this function is used draw Binary Crossentropy Loss VS No. of epochs
         plot
        def plt dynamic(x, vy, ty):
          plt.figure(figsize=(10,5))
          plt.plot(x, vy, 'b', label="Validation Loss")
          plt.plot(x, ty, 'r', label="Train Loss")
          plt.xlabel('Epochs')
          plt.ylabel('Binary Crossentropy Loss')
          plt.title('\nBinary Crossentropy Loss VS Epochs')
          plt.legend()
          plt.grid()
          plt.show()
In [0]: import keras as keras
        import tensorflow as tf
        from keras.models import Sequential
        from keras.layers import Dense,Dropout,Flatten,BatchNormalization
        from keras.layers import Conv1D, MaxPooling1D
        model=Sequential()
        model.add(Conv1D(100,kernel size=(26),activation='relu',input shape=(20
        0,26)))
        model.add(MaxPooling1D(pool size=2))
        model.add(Dropout(0.5))
        model.add(Conv1D(250,26,activation='relu'))
        model.add(MaxPooling1D(pool size=4))
        model.add(Flatten())
        model.add(Dense(11836,activation='softmax'))
        model.compile(loss=keras.losses.sparse categorical crossentropy,optimiz
        er='adam',metrics=['accuracy'])
        history=model.fit(trainarray,trainy,epochs=60,validation data=[testarra
        y,testy],batch size=128)
        WARNING: Logging before flag parsing goes to stderr.
        W0619 10:52:49.821394 139727061636992 deprecation wrapper.py:119] From
```

/usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow backen d.py:74: The name tf.get_default graph is deprecated. Please use tf.com pat.v1.get default graph instead.

W0619 10:52:49.864488 139727061636992 deprecation wrapper.py:119] From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow backen d.py:517: The name tf.placeholder is deprecated. Please use tf.compat.v 1.placeholder instead.

W0619 10:52:49.874052 139727061636992 deprecation wrapper.py:119] From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow backen d.py:4138: The name tf.random uniform is deprecated. Please use tf.rand om.uniform instead.

W0619 10:52:49.918748 139727061636992 deprecation wrapper.py:119] From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow backen d.py:3976: The name tf.nn.max pool is deprecated. Please use tf.nn.max pool2d instead.

W0619 10:52:49.928320 139727061636992 deprecation wrapper.py:119] From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow backen d.py:133: The name tf.placeholder with default is deprecated. Please us e tf.compat.v1.placeholder with default instead.

W0619 10:52:49.940415 139727061636992 deprecation.py:506] From /usr/loc al/lib/python3.6/dist-packages/keras/backend/tensorflow backend.py:344 5: calling dropout (from tensorflow.python.ops.nn ops) with keep prob i s deprecated and will be removed in a future version. Instructions for updating:

Please use `rate` instead of `keep prob`. Rate should be set to `rate = 1 - keep prob`.

W0619 10:52:50.011578 139727061636992 deprecation wrapper.py:119] From /usr/local/lib/python3.6/dist-packages/keras/optimizers.py:790: The nam e tf.train.Optimizer is deprecated. Please use tf.compat.v1.train.Optim izer instead.

W0619 10:52:50.039674 139727061636992 deprecation wrapper.py:119] From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow backen d.py:3341: The name tf.log is deprecated. Please use tf.math.log instea

```
W0619 10:52:50.175851 139727061636992 deprecation.py:323] From /usr/loc al/lib/python3.6/dist-packages/tensorflow/python/ops/math_grad.py:1250: add_dispatch_support.<locals>.wrapper (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
```

```
Train on 180000 samples, validate on 20000 samples
Epoch 1/60
s: 5.5257 - acc: 0.2277 - val loss: 2.8999 - val acc: 0.5254
Epoch 2/60
s: 2.0066 - acc: 0.6391 - val loss: 1.6602 - val acc: 0.7128
Epoch 3/60
s: 0.9869 - acc: 0.8030 - val loss: 1.3317 - val acc: 0.7723
Epoch 4/60
s: 0.6012 - acc: 0.8794 - val loss: 1.2425 - val acc: 0.7936
Epoch 5/60
s: 0.4280 - acc: 0.9166 - val loss: 1.2195 - val acc: 0.8114
Epoch 6/60
s: 0.3434 - acc: 0.9367 - val loss: 1.2495 - val acc: 0.8144
Epoch 7/60
s: 0.2966 - acc: 0.9475 - val loss: 1.2795 - val acc: 0.8261
Epoch 8/60
s: 0.2669 - acc: 0.9563 - val loss: 1.2914 - val acc: 0.8247
Epoch 9/60
s: 0.2537 - acc: 0.9602 - val loss: 1.2948 - val acc: 0.8323
Epoch 10/60
s: 0.2397 - acc: 0.9646 - val loss: 1.3121 - val acc: 0.8372
```

```
Epoch 11/60
s: 0.2320 - acc: 0.9670 - val loss: 1.3329 - val acc: 0.8395
Epoch 12/60
s: 0.2240 - acc: 0.9692 - val loss: 1.3685 - val acc: 0.8390
Epoch 13/60
s: 0.2178 - acc: 0.9714 - val loss: 1.4026 - val acc: 0.8408
Epoch 14/60
s: 0.2165 - acc: 0.9724 - val loss: 1.3675 - val acc: 0.8469
Epoch 15/60
s: 0.2119 - acc: 0.9736 - val loss: 1.4069 - val acc: 0.8476
Epoch 16/60
s: 0.2079 - acc: 0.9748 - val loss: 1.4261 - val acc: 0.8462
Epoch 17/60
s: 0.2062 - acc: 0.9758 - val loss: 1.4319 - val acc: 0.8493
Epoch 18/60
s: 0.2052 - acc: 0.9765 - val loss: 1.4688 - val acc: 0.8476
Epoch 19/60
s: 0.2040 - acc: 0.9770 - val_loss: 1.4723 - val_acc: 0.8484
Epoch 20/60
s: 0.2015 - acc: 0.9774 - val loss: 1.4961 - val acc: 0.8513
Epoch 21/60
s: 0.2020 - acc: 0.9780 - val loss: 1.4971 - val acc: 0.8522
Epoch 22/60
s: 0.1988 - acc: 0.9788 - val loss: 1.5217 - val acc: 0.8515
Epoch 23/60
s: 0.2021 - acc: 0.9788 - val loss: 1.5570 - val acc: 0.8507
Epoch 24/60
```

```
s: 0.1988 - acc: 0.9796 - val loss: 1.5296 - val acc: 0.8526
Epoch 25/60
s: 0.1992 - acc: 0.9794 - val loss: 1.5206 - val acc: 0.8585
Epoch 26/60
s: 0.1963 - acc: 0.9803 - val loss: 1.5375 - val acc: 0.8596
Epoch 27/60
s: 0.2003 - acc: 0.9802 - val loss: 1.5813 - val acc: 0.8574
Epoch 28/60
s: 0.1967 - acc: 0.9810 - val loss: 1.5897 - val acc: 0.8569
Epoch 29/60
s: 0.1982 - acc: 0.9808 - val loss: 1.6297 - val acc: 0.8561
Epoch 30/60
s: 0.1981 - acc: 0.9815 - val loss: 1.5936 - val acc: 0.8610
Epoch 31/60
s: 0.1931 - acc: 0.9823 - val loss: 1.6144 - val acc: 0.8587
Epoch 32/60
s: 0.1961 - acc: 0.9820 - val loss: 1.6397 - val acc: 0.8577
Epoch 33/60
s: 0.1988 - acc: 0.9815 - val loss: 1.6595 - val acc: 0.8570
Epoch 34/60
s: 0.1979 - acc: 0.9819 - val loss: 1.6654 - val acc: 0.8568
Epoch 35/60
s: 0.1973 - acc: 0.9824 - val loss: 1.6312 - val acc: 0.8628
Epoch 36/60
s: 0.1994 - acc: 0.9818 - val loss: 1.6544 - val acc: 0.8636
Epoch 37/60
```

```
s: 0.1984 - acc: 0.9824 - val loss: 1.7020 - val acc: 0.8570
Epoch 38/60
s: 0.2005 - acc: 0.9821 - val loss: 1.6565 - val acc: 0.8636
Epoch 39/60
s: 0.1992 - acc: 0.9828 - val loss: 1.6592 - val acc: 0.8639
Epoch 40/60
s: 0.1964 - acc: 0.9831 - val loss: 1.7462 - val acc: 0.8600
Epoch 41/60
s: 0.1998 - acc: 0.9827 - val loss: 1.7084 - val acc: 0.8648
Epoch 42/60
s: 0.1971 - acc: 0.9835 - val loss: 1.7081 - val acc: 0.8640
Epoch 43/60
s: 0.1990 - acc: 0.9831 - val loss: 1.7628 - val acc: 0.8606
Epoch 44/60
s: 0.1964 - acc: 0.9837 - val loss: 1.7827 - val acc: 0.8612
Epoch 45/60
s: 0.1979 - acc: 0.9835 - val loss: 1.7522 - val acc: 0.8627
Epoch 46/60
s: 0.2000 - acc: 0.9834 - val loss: 1.7651 - val acc: 0.8635
Epoch 47/60
s: 0.1979 - acc: 0.9838 - val loss: 1.7817 - val acc: 0.8636
Epoch 48/60
s: 0.1974 - acc: 0.9841 - val loss: 1.7953 - val acc: 0.8606
Epoch 49/60
s: 0.2005 - acc: 0.9837 - val loss: 1.7954 - val_acc: 0.8637
Epoch 50/60
```

```
s: 0.1989 - acc: 0.9841 - val loss: 1.7745 - val acc: 0.8635
    Epoch 51/60
    s: 0.2007 - acc: 0.9841 - val loss: 1.7846 - val acc: 0.8643
    Epoch 52/60
    s: 0.2015 - acc: 0.9840 - val loss: 1.7881 - val acc: 0.8660
    Epoch 53/60
    180000/180000 [==============] - 146s 812us/step - los
    s: 0.1968 - acc: 0.9846 - val loss: 1.7539 - val acc: 0.8689
    Epoch 54/60
    s: 0.1975 - acc: 0.9847 - val loss: 1.7651 - val acc: 0.8690
    Epoch 55/60
    s: 0.1984 - acc: 0.9847 - val loss: 1.8288 - val acc: 0.8648
    Epoch 56/60
    s: 0.2038 - acc: 0.9841 - val loss: 1.7976 - val acc: 0.8675
    Epoch 57/60
    s: 0.1988 - acc: 0.9846 - val loss: 1.8241 - val acc: 0.8656
    Epoch 58/60
    s: 0.1984 - acc: 0.9849 - val loss: 1.8200 - val acc: 0.8680
    Epoch 59/60
    s: 0.2062 - acc: 0.9843 - val loss: 1.8341 - val acc: 0.8671
    Epoch 60/60
    s: 0.1988 - acc: 0.9849 - val loss: 1.8329 - val acc: 0.8682
In [0]: import matplotlib.pyplot as plt
    scores = model.evaluate(testarray, testy, verbose=0)
    print("Accuracy: %.2f%" % (scores[1]*100))
```

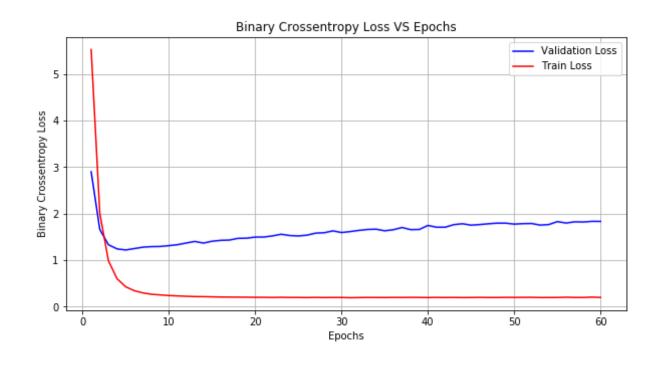
```
# Test and train accuracy of the model
model_3_test = scores[1]
model_3_train = max(history.history['acc'])

# Plotting Train and Test Loss VS no. of epochs
# list of epoch numbers
x = list(range(1,61))

# Validation loss
vy = history.history['val_loss']
# Training loss
ty = history.history['loss']

# Calling the function to draw the plot
plt_dynamic(x, vy, ty)
```

Accuracy: 86.83%



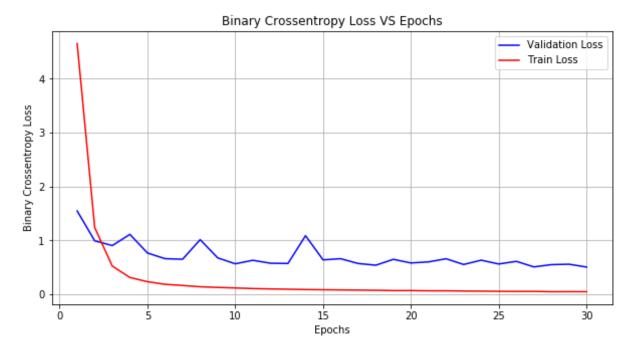
```
In [0]: import keras as keras
        import tensorflow as tf
       from keras.models import Sequential
       from keras.layers import Dense,Dropout,Flatten,BatchNormalization
       from keras.layers import Conv1D, MaxPooling1D
       model=Sequential()
       model.add(Conv1D(2000, kernel size=26, activation='relu', input shape=(200
       model.add(MaxPooling1D(pool size=2))
       model.add(Dropout(0.4))
       model.add(BatchNormalization())
       model.add(Conv1D(250,20,activation='relu'))
       model.add(MaxPooling1D(pool size=4))
       model.add(Dropout(0.6))
       model.add(BatchNormalization())
       model.add(Flatten())
       model.add(Dense(11836,activation='softmax'))
       model.compile(loss=keras.losses.sparse categorical_crossentropy,optimiz
       er='adam',metrics=['accuracy'])
       history=model.fit(trainarray,trainy,epochs=30,validation data=[testarra
       v, testyl, batch size=128)
       W0619 19:50:21.398618 139644765677440 nn ops.py:4224] Large dropout rat
       e: 0.6 (>0.5). In TensorFlow 2.x, dropout() uses dropout rate instead o
       f keep prob. Please ensure that this is intended.
       W0619 19:50:21.626489 139644765677440 deprecation.py:323] From /usr/loc
       al/lib/python3.6/dist-packages/tensorflow/python/ops/math grad.py:1250:
       add dispatch support.<locals>.wrapper (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
       Train on 180000 samples, validate on 20000 samples
       Epoch 1/30
       4.6548 - acc: 0.3767 - val loss: 1.5470 - val acc: 0.7329
       Epoch 2/30
       1.2378 - acc: 0.7697 - val loss: 0.9925 - val acc: 0.8195
       Epoch 3/30
        100000/100000 [_
```

```
0.5234 - acc: 0.8860 - val loss: 0.9045 - val acc: 0.8399
Epoch 4/30
0.3116 - acc: 0.9275 - val loss: 1.1124 - val acc: 0.8037
Epoch 5/30
0.2337 - acc: 0.9440 - val loss: 0.7667 - val acc: 0.8640
Epoch 6/30
0.1846 - acc: 0.9558 - val loss: 0.6613 - val acc: 0.8891
Epoch 7/30
0.1633 - acc: 0.9608 - val loss: 0.6504 - val acc: 0.8899
Epoch 8/30
0.1391 - acc: 0.9667 - val loss: 1.0141 - val acc: 0.8384
Epoch 9/30
0.1272 - acc: 0.9692 - val loss: 0.6761 - val acc: 0.8894
Epoch 10/30
0.1172 - acc: 0.9721 - val loss: 0.5658 - val acc: 0.9101
Epoch 11/30
0.1057 - acc: 0.9752 - val loss: 0.6312 - val acc: 0.9002
Epoch 12/30
0.0990 - acc: 0.9768 - val loss: 0.5767 - val acc: 0.9083
Epoch 13/30
0.0937 - acc: 0.9780 - val loss: 0.5718 - val acc: 0.9096
Epoch 14/30
0.0880 - acc: 0.9795 - val loss: 1.0875 - val acc: 0.8390
Epoch 15/30
0.0838 - acc: 0.9805 - val loss: 0.6391 - val acc: 0.9012
Epoch 16/30
```

```
0.0806 - acc: 0.9816 - val loss: 0.6606 - val acc: 0.8958
Epoch 17/30
0.0777 - acc: 0.9825 - val loss: 0.5714 - val acc: 0.9137
Epoch 18/30
0.0739 - acc: 0.9832 - val loss: 0.5397 - val acc: 0.9212
Epoch 19/30
0.0684 - acc: 0.9844 - val loss: 0.6490 - val acc: 0.9012
Epoch 20/30
0.0686 - acc: 0.9845 - val loss: 0.5817 - val acc: 0.9124
Epoch 21/30
0.0641 - acc: 0.9856 - val loss: 0.6012 - val acc: 0.9091
Epoch 22/30
0.0644 - acc: 0.9857 - val loss: 0.6598 - val acc: 0.9002
Epoch 23/30
0.0598 - acc: 0.9868 - val loss: 0.5533 - val acc: 0.9185
Epoch 24/30
0.0577 - acc: 0.9870 - val loss: 0.6329 - val acc: 0.9084
Epoch 25/30
0.0551 - acc: 0.9878 - val loss: 0.5622 - val acc: 0.9185
Epoch 26/30
0.0528 - acc: 0.9883 - val loss: 0.6116 - val acc: 0.9100
Epoch 27/30
0.0537 - acc: 0.9882 - val loss: 0.5081 - val acc: 0.9263
Epoch 28/30
0.0474 - acc: 0.9896 - val loss: 0.5505 - val acc: 0.9192
Epoch 29/30
```

```
0.0484 - acc: 0.9894 - val loss: 0.5581 - val acc: 0.9175
       Epoch 30/30
       0.0474 - acc: 0.9897 - val loss: 0.5054 - val acc: 0.9285
In [0]: import matplotlib.pyplot as plt
       scores = model.evaluate(testarray,testy, verbose=0)
       print("Accuracy: %.2f%" % (scores[1]*100))
       # Test and train accuracy of the model
       model 3 test = scores[1]
       model 3 train = max(history.history['acc'])
       # Plotting Train and Test Loss VS no. of epochs
       # list of epoch numbers
       x = list(range(1,31))
       # Validation loss
       vy = history.history['val loss']
       # Training loss
       ty = history.history['loss']
       # Calling the function to draw the plot
       plt dynamic(x, vy, ty)
```

Accuracy: 92.86%



```
In [0]: #do bidirectional lstm in this
        import keras as keras
        import tensorflow as tf
        from keras.models import Sequential
        from keras.layers import Dense,Dropout,Flatten,BatchNormalization
        from keras.layers import Conv1D, MaxPooling1D
        from keras.layers import LSTM, Bidirectional
        model=Sequential()
        model.add(Dense(200,activation='relu',input shape=(200,26)))
        model.add(Dropout(0.4))
        model.add(BatchNormalization())
        model.add(Bidirectional(LSTM(26,dropout=0.2,return sequences=True)))
        model.add(BatchNormalization())
        model.add(Flatten())
        model.add(Dense(11836,activation='softmax'))
        model.compile(loss=keras.losses.sparse categorical crossentropy,optimiz
        er='adam',metrics=['accuracy'])
```

history=model.fit(trainarray,trainy,epochs=3,validation_data=[testarray
,testy],batch size=128)

Using TensorFlow backend.

WARNING: Logging before flag parsing goes to stderr.

W0620 12:33:09.188477 140488317740928 deprecation_wrapper.py:119] From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backen d.py:74: The name tf.get_default_graph is deprecated. Please use tf.com pat.v1.get_default_graph instead.

W0620 12:33:09.227867 140488317740928 deprecation_wrapper.py:119] From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backen d.py:517: The name tf.placeholder is deprecated. Please use tf.compat.v 1.placeholder instead.

W0620 12:33:09.237042 140488317740928 deprecation_wrapper.py:119] From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backen d.py:4138: The name tf.random_uniform is deprecated. Please use tf.rand om.uniform instead.

W0620 12:33:09.270805 140488317740928 deprecation_wrapper.py:119] From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backen d.py:133: The name tf.placeholder_with_default is deprecated. Please us e tf.compat.v1.placeholder_with_default instead.

W0620 12:33:09.283224 140488317740928 deprecation.py:506] From /usr/loc al/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:344 5: calling dropout (from tensorflow.python.ops.nn_ops) with keep_prob i s deprecated and will be removed in a future version. Instructions for updating:

Please use `rate` instead of `keep_prob`. Rate should be set to `rate = 1 - keep prob`.

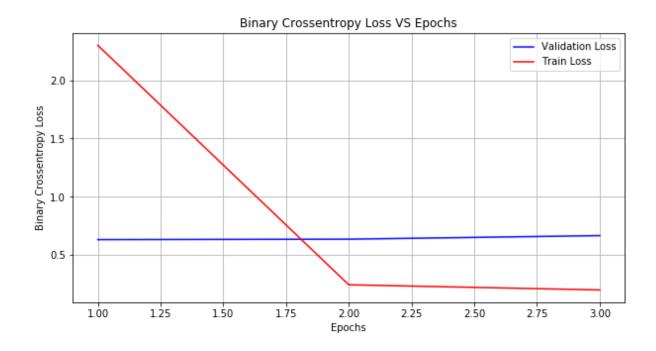
W0620 12:33:10.224582 140488317740928 deprecation_wrapper.py:119] From /usr/local/lib/python3.6/dist-packages/keras/optimizers.py:790: The nam e tf.train.Optimizer is deprecated. Please use tf.compat.v1.train.Optimizer instead.

W0620 12:33:10.256244 140488317740928 deprecation_wrapper.py:119] From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backen d.py:3341: The name tf.log is deprecated. Please use tf.math.log instea

```
d.
       W0620 12:33:10.411857 140488317740928 deprecation.py:323] From /usr/loc
       al/lib/python3.6/dist-packages/tensorflow/python/ops/math grad.py:1250:
       add dispatch support.<locals>.wrapper (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
       Train on 180000 samples, validate on 20000 samples
       Epoch 1/3
       2.2988 - acc: 0.7371 - val loss: 0.6325 - val acc: 0.9112
       Epoch 2/3
       0.2449 - acc: 0.9800 - val loss: 0.6362 - val acc: 0.9126
       Epoch 3/3
       0.2006 - acc: 0.9867 - val loss: 0.6668 - val acc: 0.9104
In [0]: import matplotlib.pyplot as plt
       scores = model.evaluate(testarray,testy, verbose=0)
       print("Accuracy: %.2f%" % (scores[1]*100))
       # Test and train accuracy of the model
       model 3 test = scores[1]
       model 3 train = max(history.history['acc'])
       # Plotting Train and Test Loss VS no. of epochs
       # list of epoch numbers
       x = list(range(1,4))
       # Validation loss
       vy = history.history['val loss']
       # Training loss
       ty = history.history['loss']
```

Calling the function to draw the plot
plt_dynamic(x, vy, ty)

Accuracy: 91.04%



*** FOR 130000 POINTS.

```
In [18]:  \begin{array}{l} \textbf{import pandas as pd} \\ s=[['\text{CONV'},'70','128','(100,250)','(0.5,0.6)','(21,26)','0.98','0.89'], \\ ['\text{CONV+LSTM'},'70','128','(300,250,300(LSTM))','(0.4,0.6,0.4)','(21,26)', \\ ['0.98','0.88'],['\text{DE+CONV+LSTM'},'70','256','(300,250,500(LSTM))','(0.7,0.7,0.4)','(26,26)','0.98','0.86'],['(\text{BI-DIR-LSTM})','5','128','(256,26), \\ [(\text{LSTM}))','(0.7,0.5)','\text{NONE'},'0.99','0.86'],['\text{CONV'},'25','256','(100,25), \\ [0','(0.2,0.2)','(10,20)','0.85','0.85'],['\text{CONV'},'80','128','(2000,250)', \\ [0.4,0.6)','(26,20)','0.98','0.9'],['\text{DEN+LSTM+DEN'},'60','128','(256,26), \\ [0,128)','(0.3,0.2,0.3)','\text{NONE'},'0.85','0.88'],['\text{CONVOLUTIONAL'},'25','256','(100,250)','(100,250)','(10,20)','0.98','0.87'],['\text{CONVOLUTIONAL'},'8] \\ \end{array}
```

0','64','(100,250)','(0.2,0.3)','(25,26)','0.85','0.89'],['CONVOLUTIONA
L','60','128','(100,250))','(0.5)','(26,26)','0.95','0.90'],['CONVOLUTI
ONAL','100','256','(1500,500,512)','(0.5,0.4,0.4)',"(21,26,1)",'0.99',
'0.9'],['CON-CON-BIDI-LSTM','60','128','(500,250,300(BI-LSTM))','(0.5,
0.7,0.4)','(26,26)','0.95','0.82'],['DENS+BIDIR-LSTM','2','128','(200,26)','(0.4,0.2)','NONE','0.98','0.89']]

x=pd.DataFrame(s,columns=['DL-TECHNIQUE','EPCHS','BCHSIZ','CONFIGURATIO
N','DRPOUT','KERN-SIZE','TRAIN ACC','TES-ACC'],index=None)
x

Out[18]:

	DL-TECHNIQUE	EPCHS	BCHSIZ	CONFIGURATION	DRPOUT	KERN- SIZE	TRAIN ACC	TES- ACC
0	CONV	70	128	(100,250)	(0.5,0.6)	(21,26)	0.98	0.89
1	CONV+LSTM	70	128	(300,250,300(LSTM))	(0.4,0.6,0.4)	(21,26)	0.98	0.88
2	DE+CONV+LSTM	70	256	(300,250,500(LSTM))	(0.7,0.7,0.4)	(26,26)	0.98	0.86
3	(BI-DIR-LSTM)	5	128	(256,26(LSTM))	(0.7,0.5)	NONE	0.99	0.86
4	CONV	25	256	(100,250	(0.2,0.2)	(10,20)	0.85	0.85
5	CONV	80	128	(2000,250)	(0.4,0.6)	(26,20)	0.98	0.9
6	DEN+LSTM+DEN	60	128	(256,26,128)	(0.3,0.2,0.3)	NONE	0.85	0.88
7	CONVOLUTIONAL	25	256	(100,250)	(0.2,0.2)	(10,20)	0.98	0.87
8	CONVOLUTIONAL	80	64	(100,250)	(0.2,0.3)	(25,26)	0.85	0.89
9	CONVOLUTIONAL	60	128	(100,250))	(0.5)	(26,26)	0.95	0.90
10	CONVOLUTIONAL	100	256	(1500,500,512)	(0.5,0.4,0.4)	(21,26,1)	0.99	0.9
11	CON-CON-BIDI- LSTM	60	128	(500,250,300(BI- LSTM))	(0.5,0.7,0.4)	(26,26)	0.95	0.82
12	DENS+BIDIR- LSTM	2	128	(200,26)	(0.4,0.2)	NONE	0.98	0.89

** FOR 180000 TRAINING SAMPLES

```
In [2]: import pandas as pd
s=[['CONVOLUTIONAL','60','128','(100,250)','(0.5)','(26,26)','0.98','0.
86'],['CONVOLUTIONAL','30','128','(2000,250)','(0.4,0.6)','(26,20)','0.
99','0.93'],['DENSE+BIDIRECTIONAL-LSTM','2','128','(200,26)','(0.4,0.
2)','NONE','0.98','0.91']]

x=pd.DataFrame(s,columns=['DL-TECHNIQUE','EPOCHS','BATCHSIZ','CONFIG',
'DRPOUT-RATE','KERN-SIZE','TRAIN-ACC','TEST-ACC'])
x
```

Out[2]:

	DL-TECHNIQUE	EPOCHS	BATCHSIZ	CONFIG	DRPOUT- RATE	KERN- SIZE	TRAIN- ACC	TEST- ACC
0	CONVOLUTIONAL	60	128	(100,250)	(0.5)	(26,26)	0.98	0.86
1	CONVOLUTIONAL	30	128	(2000,250)	(0.4,0.6)	(26,20)	0.99	0.93
2	DENSE+BIDIRECTIONAL- LSTM	2	128	(200,26)	(0.4,0.2)	NONE	0.98	0.91

OBSERVATIONS DOCUMENTATION AND KEYTAKEAWAYS.

IN PFAM RANDOM SPLIT CASE STUDY WE ARE GIVEN WITH SEQUENCE AND WE HAVE TO PREDICT THE FMILY OF THE PROTEIN. WE HAVE TO PREDICT THE FAMILY PROTEIN.

WE HAVE THE INPUT FEATURES TO OUR MODEL .AMINO ACID IS THE SEQUENCE FOR THIS DOMAIN.

Description of fields: - sequence: These are usually the input features to your model. Amino acid sequence for this domain. There are 20 very common amino acids (frequency > 1,000,000), and 4 amino acids that are quite uncommon: X, U, B, O, Z. -

family_accession: These are usually the labels for your model. Accession number in form PFxxxxx.y (Pfam), where xxxxx is the family accession, and y is the version number.

WE HAVE DATA FOR TRAINING ,CROSS VALIDATION AND TESTING SEPERATELY. WE HAVE DONE EXPLORATORY DATA ANALTYSIS FOR DATA. WE HAVE 1100 CLASS LABELS WHICH ARE VERY FREQUENT.

OBSERVATIONS ARE FEW FAMILY ACCESSIONS ARE SIMILAR

FROM THE EXPLOARTORY DATA ANLYSIS HISTOGRAM PLOTS OF WE HAVE VISUALISED SEQUENCE LENGTH THE TRAIN DATA, TEST DATA AND CROSS VALIDATION DATA.

WE HAVE VISUALISED THE BOXPLOT AND VIOLIN PLOT FOR THE ALIGNMENT LENGTH.

WE HAVE PLOTTED THE PROBABILITY DENSITY FUNCTION AND CONSIDERD THE LENGTH OF SEQUENCE.WE HAVE CONSIDERD THE LENGTH OF 200 DUE TO LACK OF COMPUTATIONAL POWER, WE HAVE ALSO PLOTTED THE LENGTH OF SEQUENCE.

WE HAVE ENCODED EVERY LETTER OF SEQUENCE INTO LENGTH OF 26. WE HAVE OBTAINED THE SEQUENCE PATTERN AND DETERMINED THE CLASS LABEL.

THERE ARE FEW KEY TAKE AWAYS

- SEQUEENCE LENGTH IS ALMOST SIMILAR FOR THE PARTICULAR CLASS LABEL.
- THE SEQUENCE OF THE PROTEIN FOLLOW A PATTERN.

WE WILL TRAINED THE MODEL USING THE CONVOLUTIONAL NERAL NETWORS FROM THE FEATURES WE EXTRACT TO PREDICT THE CLASSLABEL.

OBSERVATIONS AFTER PERFORMING FEATURE EXTRACTION:-

- ** UNIQUE CLASS LABELS HAVE UNIQUE LENGTH OF SEQUENCE
- ** THE SEQUENCE WHICH ARE REPRESENTED BY THE UNDEFINED DOTS THEIR INDICES ARE ALMOST SIMILAR FOR THAT PARTICULAR CLASSLABEL.

THERE ARE VARIOUS RESEARCH PAPERS, BLOGS, YOUTUBE VIDEOS WHICH DESCRIBE THE REALTION OF PROTEIN SEQUENCES..

ALL THE ANLAYSIS WE HAVE DONE IS PART OF PROTEIN SEQUENCING TO PREDICT WHETHER THAT PROTEIN SEQUENCE BELONGS TO PARTICULAR FAMILY OR NOT.

WE HAVE USED VARIOUS CONFIGURATIONS WE HAVE OBTAINED THE MAXIMUM ACCURACY OF PERCENT.

WE HAVE USED RELU AS THE ACTIVATION FUNCTION FOR THE INPUT AND HIDDEN LAYERS AND SOFTMAX AS THE ACTIVATION FUNCTION TO PREDICT FOR THE OUTPUT LAYER BASED ON PROBABILTY.

WE CONSIDERD ACCURACY AS THE METRIC. WE HAVE PLOTTED THE GRAPHS FOR THE TRAINLOSS AND CROSS VALIDATION LOSS TO SEE THE HOW MODEL IS PERFORMING AND WHETHER THE MODEL IS OVERFITTING OR UNDERFITTING.

WE HAVE USED DROPUTS AND BATCH NORMALIZATION WHICH ARE USED TO PREVENT THE OVERFITTING OF THE MODEL.

USING THE DROPOUT LAYER WE CAN SWITCH OFF THE CELLS OF LAYER BASED ON THE PROBABILITY GIVEN.

WE HAVE TRAINED THE MODEL ON 130000 SAMPLES OF TRAIN DATA. WE HAVE USED VARIOUS DEEP LEARNING TECHNUIQUES FROM THE MULTI LAYER PERCEPTRONS, CONVOLUTIONAL NUERAL NETWORKS, VARIOUS ARCHITECTURES OF CONVOLUTIONAL NYUERAL NETWROKS SPECIALLY INSPIRED BY RESIDUAL NETWORKS AND EXTRACTION OF BOTTLENECK FEATURES USING THE DILATION RATE AS 2.

WE HAVE ALSO DONE THE LSTM LAYER (LONG-SHORT-TERM MERMORY) AND THE BIDIRECTIONAL LSTM WITH VARYING THE NUMER OF EPOCHS, BATCH SIZE KERNEL SIZE (IN CASE OF CNN) WITH DIFFERENT DROPOUT RATES .WE HAVE USED BOTH CNN

ALONG WITH BIDIRECTIONAL LSTM AND LSTM IN SOME CASES. WE HAVE OBTAINED THE ACCURACY OF 90 PERCENTAGE USING THE CONVOLUTIONAL NUERAL NETS AND BIDIRECTIONAL LSTMS.

WE HAVE ALSO USED 180000 TRAINING SAMPLES DIRECTLY UPLOADED IN THE DRIVE PROCESSING IN LATOP OF 32 GB RAM. USING THE 180000 TRAINING SAMPLES WE HAVE ACHIEVED THE ACCURACY OF APPROXIMATELY 93 PERCENTAGE(0.928) WITH CONVOLUTIONAL NUERAL NETWORKS.

THIS ARE THE DEEPLEARNING TECHNIQUES THAT ARE USED WHICH ARE BETTER THEAN THE HIDDEN MARKOV MODELS TAKES LESS TIME AND COMPUTATION POWER AND ACHIEVE BEST RESULTS.

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