Assignment14: LSTM

LSTM model on Amazon Fine Food Reviews

Objective:

- Apply LSTM model with different architectures & number of layers on Amazon food reviews.
- Plots Traing and testing error plot.

In [0]:
```
import warnings
warnings.filterwarnings("ignore")
```

In [0]:
```
%matplotlib inline
import re
from datetime import datetime
import math
import pandas as pd
import numpy as np
import nltk
import string
import pickle
import matplotlib.pyplot as plt

import seaborn as sns

from sklearn.feature_extraction.text import CountVectorizer
from nltk.stem.porter import PorterStemmer


from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
```

```
from nltk.stem.wordnet import WordNetLemmatizer

from gensim.models import Word2Vec
from gensim.models import KeyedVectors
```

In [0]:
```
# Importing libraries
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import LSTM
from keras.layers.embeddings import Embedding
from keras.preprocessing import sequence
from keras.layers import Dropout
# fix random seed for reproducibility
np.random.seed(7)
```

```
Using TensorFlow backend.
```

In [0]:
```
%matplotlib inline
import matplotlib.pyplot as plt
import numpy as np
import time
# https://gist.github.com/greydanus/f6eee59eaf1d90fcb3b534a25362cea4
# https://stackoverflow.com/a/14434334
# this function is used to update the plots for each epoch and error
def plt_dynamic(x, vy, ty):
  fig = plt.figure( facecolor='c', edgecolor='k')
  plt.plot(x, vy, 'b', label="Validation Loss")
  plt.plot(x, ty, 'r', label="Train Loss")
  plt.xlabel('Epochs')
  plt.ylabel('Categorical Crossentropy Loss')
  plt.legend()
  plt.grid()
  plt.show()
```

To upload the reviews.zip file from system to google colab

In [0]:
```
# Reference link
# https://towardsdatascience.com/3-ways-to-load-csv-files-into-colab-7c14fcbdcb92
# Code to read csv file into Colaboratory:
!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)
```

```
    100% |████████████████████████████████| 993kB 19.7MB/s
  Building wheel for PyDrive (setup.py) ... done
```

In [0]:
```
link = 'https://drive.google.com/file/d/1p5YpkUos0Rd6Hsae1qaH0VsPtnLdlnc0/view?usp=sharing'
```

In [0]:
```
fluff, id = link.split('=')
id='1p5YpkUos0Rd6Hsae1qaH0VsPtnLdlnc0'
print (id)
```

```
1p5YpkUos0Rd6Hsae1qaH0VsPtnLdlnc0
```

In [0]:
```
 downloaded = drive.CreateFile({'id':id})
downloaded.GetContentFile('Reviews.csv')
```

In [0]:
```
amz = pd.read_csv('Reviews.csv')
# dimensions of dataset and columns name
print(amz.shape)
#print(amz1.shape)
print(amz.columns)
```

```
(568454, 10)
Index(['Id', 'ProductId', 'UserId', 'ProfileName', 'HelpfulnessNumerato
```

```
r',
       'HelpfulnessDenominator', 'Score', 'Time', 'Summary', 'Text'],
      dtype='object')
```

Given reviews with Score>3 a positive rating, and reviews with a score<3 a negative rating. If score is equal to 3,it is considered as neutral score.

In [0]:
```
# Processing
#Give reviews with Score>3 a positive rating, and reviews with a score<
3 a negative rating.

def score_part(x):
    if x < 3:
        return 0
    return 1

actualScore = amz['Score']
#print(actualScore)
New_score = actualScore.map(score_part)
#print(New_score)
amz['Score']=New_score
```

In [0]:
```
print(amz.shape)
amz.head(2)
```

```
(568454, 10)
```

Out[0]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfulnes
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfulnes
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0

Data Pre-processing on raw data:

Every datasets contains some unwanted data.Raw data is preprocessed by removing duplication.

In [0]:
```
#Processing of ProductId
#Sorting data according to ProductId in ascending order
sorted_data=amz.sort_values('ProductId', axis=0, ascending=True,
                            inplace=False, kind='quicksort',
                            na_position='last')
#sorted_data.head() # printing sorted data
# To check the duplications in raw data
dupli=sorted_data[sorted_data.duplicated(["UserId","ProfileName","Time"
,"Text"])]
print(dupli.head(2))
# Remove Deduplication of entries
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time"
,"Text"}, keep='first', inplace=False)
final.shape
#Checking to see how much % of data still remains
(final['Id'].size*1.0)/(amz['Id'].size*1.0)*100
final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
#Before starting the next phase of preprocessing lets see the number of
 entries left
print(final.shape)
```

```
             Id   ProductId          UserId  \
171222  171223  7310172001  AJD41FBJD9010
171153  171154  7310172001  AJD41FBJD9010

                                       ProfileName  HelpfulnessNumera
tor  \
171222  N. Ferguson "Two, Daisy, Hannah, and Kitten"
  1
171153  N. Ferguson "Two, Daisy, Hannah, and Kitten"
  0

        HelpfulnessDenominator  Score        Time  \
171222                       1      1  1233360000
171153                       0      1  1233360000

                                                Summary  \
171222  best dog treat-- great for training---  all do...
171153  best dog treat-- great for training---  all do...

                                                   Text
171222  Freeze dried liver has a hypnotic effect on do...
171153  Freeze dried liver has a hypnotic effect on do...
(393931, 10)
```

In [0]:
```
final = final[final['ProductId'] != '7310172001']
```

Text Preprocessing:

In [0]:
```
import nltk
nltk.download('stopwords')
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
```

Out[0]: True

In [0]:
```
```

```
stop = set(stopwords.words('english')) #set of stopwords
sno = nltk.stem.SnowballStemmer('english') #initialising the snowball s
temmer

def cleanhtml(sentence): #function to clean the word of any html-tags
    cleanr = re.compile('<.*?>$< /><')
    #cleanr = re.compile('<.*?>')
    cleantext = re.sub(cleanr, ' ', sentence)
    return cleantext
def cleanpunc(sentence): #function to clean the word of any punctuation
 or special characters
    cleaned = re.sub(r'[?|!|\'|"|#]',r'',sentence)
    cleaned = re.sub(r'[.|,|)|(|\|/]',r' ',cleaned)
    return  cleaned
```

In [0]:

```
#Code for implementing step-by-step the checks mentioned in the pre-pro
cessing phase.

'''Pre processing of text data:It is cleaning and flitering text'''
i=0
str1=' '
global final_string
final_string=[]
all_positive_words=[]
all_negative_words=[]
s=''
for sent in final['Text'].values:
    filtered_sentence=[]
    #print(sent);
    sent=cleanhtml(sent) # remove HTml tags
    for w in sent.split():
        for cleaned_words in cleanpunc(w).split():
            if((cleaned_words.isalpha()) & (len(cleaned_words)>2)):
                if(cleaned_words.lower() not in stop):
                    s=(sno.stem(cleaned_words.lower())).encode('utf8')
                    filtered_sentence.append(s)
                    if (final['Score'].values)[i] == 1:
                        all_positive_words.append(s) #list of all words
 used to describe positive reviews
```

```
                    if(final['Score'].values)[i] == 0:
                        all_negative_words.append(s) #list of all words
 used to describe negative reviews reviews
                else:
                    continue
            else:
                continue
    #print(filtered_sentence)
    str1 = b" ".join(filtered_sentence) #final string of cleaned words
    #print("**********************************************************
************")

    final_string.append(str1)
    i+=1
```

Dumping and loading Pre processing of text data in pickle file

In [0]:
```
pickle_path_final_string='final_string.pkl'
final_string_file=open(pickle_path_final_string,'wb')
pickle.dump(final_string,final_string_file)
final_string_file.close()
```

In [0]:
```
pickle_path_final_string='final_string.pkl'
final_string_unpkl=open(pickle_path_final_string,'rb')
final_string=pickle.load(final_string_unpkl)
```

In [0]:
```
final['CleanedText']=final_string
final['CleanedText']=final['CleanedText'].str.decode("utf-8")
#below the processed review can be seen in the CleanedText Column
print('Shape of final',final.shape)
final.head()
```

```
Shape of final (393761, 11)
```

Out[0]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	He

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	He
150528	150529	0006641040	A25ACLV5KPB4W	Matt Hetling "Matt"	0	1
150506	150507	0006641040	A1S4A3IQ2MU7V4	sally sue "sally sue"	1	1
150505	150506	0006641040	A2IW4PEEKO2R0U	Tracy	1	1
150504	150505	0006641040	A2PTSM496CF40Z	Jason A. Teeple "Nobody made a greater mistak...	1	1
150503	150504	0006641040	AQEYF1AXARWJZ	Les Sinclair "book maven"	1	1

Converting Reviews Data into IMDB Dataset

In [0]:
```
##Sorting data according to Time in ascending order
## Time Based Splitting
time_sorted_data = final.sort_values('Time', axis=0,
                                     ascending=True,
                                     inplace=False,
                                     kind='quicksort',
                                     na_position='last')

x = time_sorted_data['CleanedText'].values
y = time_sorted_data['Score']

#  vocabulary of words using countvectorizer
count_vect = CountVectorizer()
count_vect.fit(x)

vocabulary = count_vect.get_feature_names()
print('No. of words in the Vocabulary : ',len(vocabulary))
```

```
No. of words in the Vocabulary :  73405
```

In [0]:
```
# Storing words in vocabary
word_dict=dict()
index=0
for words in x:
  for word in words.split():
    word_dict.setdefault(word,[])
    word_dict[word].append(index)
    index+=1


# Getting frequency for each word of vocabulary

freq = []
for w in vocabulary:
  freq.append(len(word_dict[w]))
```

```
print("done")
```

```
done
```

In [0]:
```
# sort the frequency in decending order

new_index=np.argsort(np.array(freq))[::-1]
```

In [0]:
```
# Allocate rank to freq in decending order
word_rank=dict()
rank=1
for i in new_index:
  word_rank[vocabulary[i]]=rank
  rank+=1
```

converting data into imdb format

In [0]:
```
review_data=[]
for sent in x:
  row=[]
  for word in sent.split():
    if len(word)>1 :
      row.append(word_rank[word])
  review_data.append(row)
```

In [0]:
```
# Splitting the data into 60-40 train_data and test_data
from sklearn.model_selection import train_test_split
X_train, X_test, Y_train, Y_test = train_test_split(review_data, y,
                                                    test_size=0.5,
                                                    random_state=42)
```

In [0]:
```
print("length of X_train :",len(X_train))
print("length of  X_test :",len(X_test))
print("Shape of Y_train :",Y_train.shape)
print("Shape of Y_test :",Y_test.shape)
```

```
length of X_train : 196880
length of  X_test : 196881
Shape of Y_train : (196880,)
Shape of Y_test : (196881,)
```

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

```
[13351, 27, 1106, 14, 379, 2444, 3182, 13972, 1142, 1241, 545, 109, 384
5, 7102, 860, 800, 10363, 1852, 11939, 8, 174, 780, 1106, 1082, 2807, 1
211, 1106, 1429, 1860, 379, 79, 263, 13972, 1438, 1699]
```

In [0]:
```
# truncate and/or pad input sequences
max_review_length = 120
X_train = sequence.pad_sequences(X_train, maxlen=max_review_length)
X_test = sequence.pad_sequences(X_test, maxlen=max_review_length)

print(X_train.shape)
print(X_train[1])
print(X_test.shape)
```

```
(196880, 120)
[    0     0     0     0     0     0     0     0     0     0     0
0
     0     0     0     0     0     0     0     0     0     0     0
0
     0     0     0     0     0     0     0     0     0     0     0
0
     0     0     0     0     0     0     0     0     0     0     0
0
     0     0     0     0     0     0     0     0     0     0     0
0
     0     0     0     0     0     0     0     0     0     0     0
0
     0     0     0     0     0     0     0     0     0     0     0    3
7
   293  1255  2912   478    29    41    26   639  2978   412  3887    91
9
  1305  1753    87   287   378   328   582   172   419   326   117     4
1
```

```
  2610   410  1399   826   631   113  1386  1014 10807   478    62     5
0]
(196881, 120)
```

In [0]:
```
len_voc=len(vocabulary)+1
print(len_voc)
```

```
73406
```

1 RNN with 1 LSTM layer

In [0]:
```
start = datetime.now()
embedding_len=32
lstm_1=Sequential()
lstm_1.add(Embedding(len_voc,
                     embedding_len,
                     input_length=max_review_length))

lstm_1.add(Dropout(0.15))

lstm_1.add(LSTM(100))# Adding first LSTM layer


lstm_1.add(Dropout(0.25))# Adding Dropout


lstm_1.add(Dense(1, activation='sigmoid'))# Adding output layer

# Printing the model summary
print(lstm_1.summary())

# Compiling the model
lstm_1.compile(loss='binary_crossentropy',
               optimizer='adam',
               metrics=['accuracy'])

# Fitting the data to the model
```

```
history_1 = lstm_1.fit(X_train, Y_train, nb_epoch=10,
                       batch_size=512 ,verbose=1,
                      validation_data=(X_test, Y_test))
#evaluating model
score=lstm_1.evaluate(X_test,Y_test,verbose=0)
test_score_lstm_1=score[0]
test_accuracy_lstm_1=score[1]
train_accuracy_lstm_1=max(history_1.history['acc'])
print('test score :',test_score_lstm_1)
print('test Accuracy :',test_accuracy_lstm_1)

# error plot
x=list(range(1,11))
vy=history_1.history['val_loss'] #validation loss
ty=history_1.history['loss'] # train loss
plt_dynamic(x, vy, ty)

runtime_lstm1=datetime.now() - start
print("Time taken to run this cell :", runtime_lstm1)
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_2 (Embedding)      (None, 120, 32)           2348992
_________________________________________________________________
dropout_2 (Dropout)          (None, 120, 32)           0
_________________________________________________________________
lstm_2 (LSTM)                (None, 100)               53200
_________________________________________________________________
dropout_3 (Dropout)          (None, 100)               0
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 101
=================================================================
Total params: 2,402,293
Trainable params: 2,402,293
Non-trainable params: 0
_________________________________________________________________
None
Train on 196880 samples, validate on 196881 samples
Epoch 1/10
```

```
196880/196880 [==============================] - 518s 3ms/step - loss:
0.2768 - acc: 0.8921 - val_loss: 0.2240 - val_acc: 0.9087
Epoch 2/10
196880/196880 [==============================] - 514s 3ms/step - loss:
0.2053 - acc: 0.9167 - val_loss: 0.2170 - val_acc: 0.9118
Epoch 3/10
196880/196880 [==============================] - 514s 3ms/step - loss:
0.1906 - acc: 0.9228 - val_loss: 0.2179 - val_acc: 0.9115
Epoch 4/10
196880/196880 [==============================] - 514s 3ms/step - loss:
0.1791 - acc: 0.9273 - val_loss: 0.2237 - val_acc: 0.9081
Epoch 5/10
196880/196880 [==============================] - 513s 3ms/step - loss:
0.1680 - acc: 0.9320 - val_loss: 0.2284 - val_acc: 0.9097
Epoch 6/10
196880/196880 [==============================] - 514s 3ms/step - loss:
0.1575 - acc: 0.9369 - val_loss: 0.2372 - val_acc: 0.9095
Epoch 7/10
196880/196880 [==============================] - 515s 3ms/step - loss:
0.1467 - acc: 0.9412 - val_loss: 0.2480 - val_acc: 0.9067
Epoch 8/10
196880/196880 [==============================] - 513s 3ms/step - loss:
0.1377 - acc: 0.9453 - val_loss: 0.2476 - val_acc: 0.9046
Epoch 9/10
196880/196880 [==============================] - 513s 3ms/step - loss:
0.1293 - acc: 0.9487 - val_loss: 0.2737 - val_acc: 0.9039
Epoch 10/10
196880/196880 [==============================] - 513s 3ms/step - loss:
0.1226 - acc: 0.9516 - val_loss: 0.2672 - val_acc: 0.9036
test score : 0.26717215862544025
test Accuracy : 0.9035559551207034
```


```
Time taken to run this cell : 1:27:53.818856
```

Observation:

- After looking at training and testing error plot, model can be diagonised as overfitting.
- Traing error slopes down while validation error also slopes and hit at inflection point.
- After the inflection point , validation loss slpoes continuously increasing.

2 RNN with 2 LSTM layer

In [0]:
```
from keras.layers.normalization import BatchNormalization
```

In [0]:
```
start = datetime.now()
embedding_len=32
lstm_2=Sequential()
lstm_2.add(Embedding(len_voc,
                     embedding_len,
                     input_length=max_review_length))
```

```
lstm_2.add(Dropout(0.15))


lstm_2.add(LSTM(100,return_sequences=True,
                dropout=0.15,
                recurrent_dropout=0.25))# Adding first LSTM layer

lstm_2.add(BatchNormalization())
lstm_2.add(LSTM(100,
                dropout=0.15,
                recurrent_dropout=0.25))# Adding second LSTM layer



#lstm_2.add(BatchNormalization())
lstm_2.add(Dense(1, activation='sigmoid'))# Adding output layer

# Printing the model summary
print(lstm_2.summary())

# Compiling the model
lstm_2.compile(loss='binary_crossentropy',
                optimizer='adam',
                metrics=['accuracy'])

# Fitting the data to the model
history_2 = lstm_2.fit(X_train, Y_train, nb_epoch=10,
                       batch_size=512 ,verbose=1,
                       validation_data=(X_test, Y_test))
runtime_lstm2=datetime.now() - start
print("Time taken to run this cell :", runtime_lstm2)
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_1 (Embedding)      (None, 120, 32)           2348992
_________________________________________________________________
dropout_1 (Dropout)          (None, 120, 32)           0
_________________________________________________________________
lstm_1 (LSTM)                (None, 120, 100)          53200
```

```
_________________________________________________________________
batch_normalization_1 (Batch (None, 120, 100)          400
_________________________________________________________________
lstm_2 (LSTM)                (None, 100)               80400
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 101
=================================================================
Total params: 2,483,093
Trainable params: 2,482,893
Non-trainable params: 200
_________________________________________________________________
None
Train on 196880 samples, validate on 196881 samples
Epoch 1/10
196880/196880 [==============================] - 1611s 8ms/step - loss:
0.2601 - acc: 0.8945 - val_loss: 0.2188 - val_acc: 0.9100
Epoch 2/10
196880/196880 [==============================] - 1596s 8ms/step - loss:
0.2043 - acc: 0.9166 - val_loss: 0.2135 - val_acc: 0.9126
Epoch 3/10
196880/196880 [==============================] - 1598s 8ms/step - loss:
0.1856 - acc: 0.9242 - val_loss: 0.2161 - val_acc: 0.9115
Epoch 4/10
196880/196880 [==============================] - 1599s 8ms/step - loss:
0.1699 - acc: 0.9311 - val_loss: 0.2251 - val_acc: 0.9111
Epoch 5/10
196880/196880 [==============================] - 1596s 8ms/step - loss:
0.1566 - acc: 0.9369 - val_loss: 0.2413 - val_acc: 0.9114
Epoch 6/10
196880/196880 [==============================] - 1600s 8ms/step - loss:
0.1450 - acc: 0.9415 - val_loss: 0.2553 - val_acc: 0.9096
Epoch 7/10
196880/196880 [==============================] - 1596s 8ms/step - loss:
0.1350 - acc: 0.9458 - val_loss: 0.2429 - val_acc: 0.9088
Epoch 8/10
196880/196880 [==============================] - 1598s 8ms/step - loss:
0.1261 - acc: 0.9495 - val_loss: 0.2651 - val_acc: 0.9091
Epoch 9/10
196880/196880 [==============================] - 1600s 8ms/step - loss:
```

```
0.1187 - acc: 0.9524 - val_loss: 0.2743 - val_acc: 0.9037
Epoch 10/10
196880/196880 [==============================] - 1599s 8ms/step - loss:
0.1116 - acc: 0.9550 - val_loss: 0.3064 - val_acc: 0.9087
Time taken to run this cell : 4:26:38.657956
```

In [0]:
```
#evaluating model
score=lstm_2.evaluate(X_test,Y_test,verbose=0)
test_score_lstm_2=score[0]
test_accuracy_lstm_2=score[1]
train_accuracy_lstm_2=max(history_2.history['acc'])
print('test score :',test_score_lstm_2)
print('test Accuracy :',test_accuracy_lstm_2)
# error plot
x=list(range(1,11))
vy=history_2.history['val_loss'] #validation loss
ty=history_2.history['loss'] # train loss
plt_dynamic(x, vy, ty)
```

```
test score : 0.3063991781577867
test Accuracy : 0.9087469080313448
```

3 RNN with 4 LSTM layer

In [0]:
```
start = datetime.now()
embedding_len=32
lstm_4=Sequential()
lstm_4.add(Embedding(len_voc,
                     embedding_len,
                     input_length=max_review_length))

lstm_4.add(Dropout(0.25))


lstm_4.add(LSTM(100,return_sequences=True,
                dropout=0.15,
                recurrent_dropout=0.25))# Adding first LSTM layer
lstm_4.add(LSTM(80,return_sequences=True,
                dropout=0.15,
                recurrent_dropout=0.25))# Adding second LSTM layer


lstm_4.add(BatchNormalization())
lstm_4.add(LSTM(50,return_sequences=True,
                dropout=0.15,
                recurrent_dropout=0.25))# Adding Third LSTM layer
lstm_4.add(BatchNormalization())
lstm_4.add(LSTM(40,
                dropout=0.15))# Adding Fourth LSTM layer
lstm_4.add(BatchNormalization())


lstm_4.add(Dense(1, activation='sigmoid'))# Adding output layer

# Printing the model summary
print(lstm_4.summary())

# Compiling the model
lstm_4.compile(loss='binary_crossentropy',
                optimizer='adam',
```

```
                metrics=['accuracy'])

# Fitting the data to the model
history_4 = lstm_4.fit(X_train, Y_train, nb_epoch=10,
                       batch_size=512 ,verbose=1,
                       validation_data=(X_test, Y_test))
runtime_lstm4=datetime.now() - start
print("Time taken to run this cell :", runtime_lstm4)
```

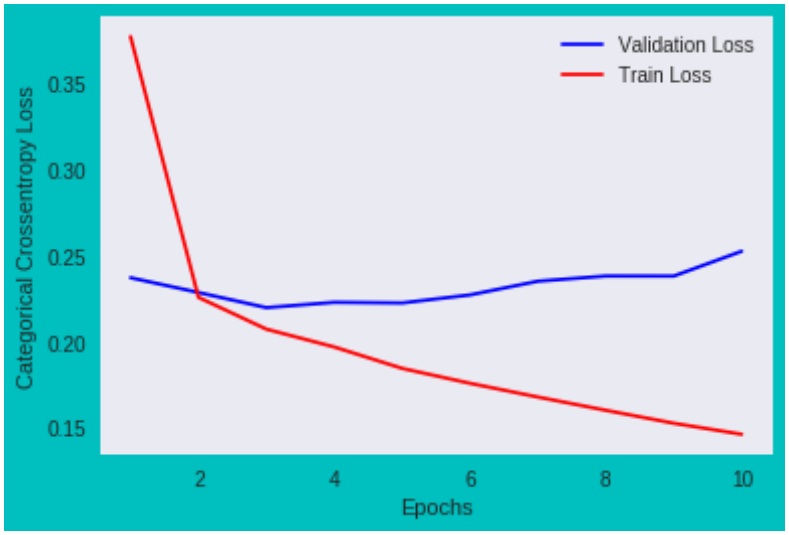
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_1 (Embedding)      (None, 120, 32)           2348992
_________________________________________________________________
dropout_1 (Dropout)          (None, 120, 32)           0
_________________________________________________________________
lstm_1 (LSTM)                (None, 120, 100)          53200
_________________________________________________________________
lstm_2 (LSTM)                (None, 120, 80)           57920
_________________________________________________________________
batch_normalization_1 (Batch (None, 120, 80)           320
_________________________________________________________________
lstm_3 (LSTM)                (None, 120, 50)           26200
_________________________________________________________________
batch_normalization_2 (Batch (None, 120, 50)           200
_________________________________________________________________
lstm_4 (LSTM)                (None, 40)                14560
_________________________________________________________________
batch_normalization_3 (Batch (None, 40)                160
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 41
=================================================================
Total params: 2,501,593
Trainable params: 2,501,253
Non-trainable params: 340
_________________________________________________________________
None
Train on 196880 samples, validate on 196881 samples
Epoch 1/10
196880/196880 [==============================] - 2089s 11ms/step - los
```

```
s: 0.3766 - acc: 0.8375 - val_loss: 0.2369 - val_acc: 0.9066
Epoch 2/10
196880/196880 [==============================] - 2081s 11ms/step - los
s: 0.2255 - acc: 0.9095 - val_loss: 0.2283 - val_acc: 0.9058
Epoch 3/10
196880/196880 [==============================] - 2087s 11ms/step - los
s: 0.2071 - acc: 0.9165 - val_loss: 0.2195 - val_acc: 0.9096
Epoch 4/10
196880/196880 [==============================] - 2091s 11ms/step - los
s: 0.1967 - acc: 0.9209 - val_loss: 0.2226 - val_acc: 0.9094
Epoch 5/10
196880/196880 [==============================] - 2090s 11ms/step - los
s: 0.1843 - acc: 0.9261 - val_loss: 0.2223 - val_acc: 0.9107
Epoch 6/10
196880/196880 [==============================] - 2085s 11ms/step - los
s: 0.1757 - acc: 0.9296 - val_loss: 0.2269 - val_acc: 0.9115
Epoch 7/10
196880/196880 [==============================] - 2080s 11ms/step - los
s: 0.1677 - acc: 0.9328 - val_loss: 0.2349 - val_acc: 0.9041
Epoch 8/10
196880/196880 [==============================] - 2081s 11ms/step - los
s: 0.1600 - acc: 0.9363 - val_loss: 0.2379 - val_acc: 0.9096
Epoch 9/10
196880/196880 [==============================] - 2082s 11ms/step - los
s: 0.1525 - acc: 0.9392 - val_loss: 0.2378 - val_acc: 0.9086
Epoch 10/10
196880/196880 [==============================] - 2084s 11ms/step - los
s: 0.1461 - acc: 0.9424 - val_loss: 0.2522 - val_acc: 0.9075
Time taken to run this cell : 5:47:39.955757
```

In [0]:
```
#evaluating model
score=lstm_4.evaluate(X_test,Y_test,verbose=0)
test_score_lstm_4=score[0]
test_accuracy_lstm_4=score[1]
train_accuracy_lstm_4=max(history_4.history['acc'])
print('test score :',test_score_lstm_4)
print('test Accuracy :',test_accuracy_lstm_4)
# error plot
x=list(range(1,11))
```

```
vy=history_4.history['val_loss'] #validation loss
ty=history_4.history['loss'] # train loss
plt_dynamic(x, vy, ty)
```

```
test score : 0.2522423982056529
test Accuracy : 0.9075177391425236
```



4 RNN with 5 LSTM layer

In [0]:
```
start = datetime.now()
embedding_len=32
lstm_5=Sequential()
lstm_5.add(Embedding(len_voc,
                     embedding_len,
                     input_length=max_review_length))

lstm_5.add(Dropout(0.45))

lstm_5.add(LSTM(120,return_sequences=True,
                dropout=0.35,
                recurrent_dropout=0.25))# Adding first LSTM layer
```

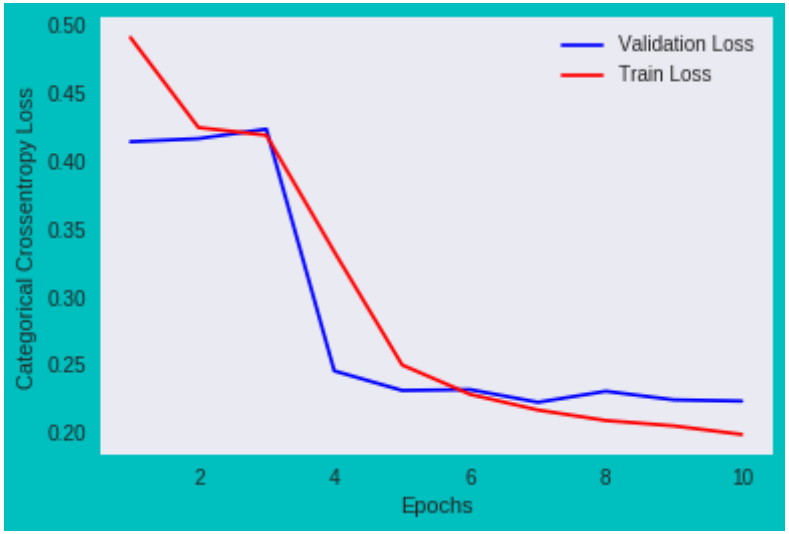
```
lstm_5.add(LSTM(100,return_sequences=True,
               dropout=0.35,
               recurrent_dropout=0.35))# Adding second LSTM layer
lstm_5.add(BatchNormalization())
lstm_5.add(LSTM(100,return_sequences=True,
               dropout=0.35,
               recurrent_dropout=0.35))# Adding Third LSTM layer
lstm_5.add(BatchNormalization())
lstm_5.add(LSTM(80,return_sequences=True,
               dropout=0.35,
               recurrent_dropout=0.35))# Adding Fourth LSTM layer
lstm_5.add(BatchNormalization())
lstm_5.add(LSTM(60,dropout=0.35,
               recurrent_dropout=0.35))# Adding Fifth LSTM layer
lstm_5.add(BatchNormalization())
lstm_5.add(Dense(1, activation='sigmoid'))# Adding output layer

# Printing the model summary
print(lstm_5.summary())

# Compiling the model
lstm_5.compile(loss='binary_crossentropy',
               optimizer='adam',
               metrics=['accuracy'])

# Fitting the data to the model
history_5 = lstm_5.fit(X_train, Y_train, nb_epoch=10,
                       batch_size=512 ,verbose=1,
                       validation_data=(X_test, Y_test))
#evaluating model
score=lstm_5.evaluate(X_test,Y_test,verbose=0)
test_score_lstm_5=score[0]
test_accuracy_lstm_5=score[1]
train_accuracy_lstm_5=max(history_5.history['acc'])
print("Train Accuracy",train_accuracy_lstm_5)
print('test score :',test_score_lstm_5)
print('test Accuracy :',test_accuracy_lstm_5)
# error plot
x=list(range(1,11))
```

```
vy=history_5.history['val_loss'] #validation loss
ty=history_5.history['loss'] # train loss
plt_dynamic(x, vy, ty)
runtime_lstm5=datetime.now() - start
print("Time taken to run this cell :", runtime_lstm5)
```

```
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/tensorfl
ow/python/framework/op_def_library.py:263: colocate_with (from tensorfl
ow.python.framework.ops) is deprecated and will be removed in a future
version.
Instructions for updating:
Colocations handled automatically by placer.
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/ba
ckend/tensorflow_backend.py:3445: calling dropout (from tensorflow.pyth
on.ops.nn_ops) with keep_prob is deprecated and will be removed in a fu
ture version.
Instructions for updating:
Please use `rate` instead of `keep_prob`. Rate should be set to `rate =
1 - keep_prob`.
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_1 (Embedding)      (None, 120, 32)           2348992
_________________________________________________________________
dropout_1 (Dropout)          (None, 120, 32)           0
_________________________________________________________________
lstm_1 (LSTM)                (None, 120, 120)          73440
_________________________________________________________________
lstm_2 (LSTM)                (None, 120, 100)          88400
_________________________________________________________________
batch_normalization_1 (Batch (None, 120, 100)          400
_________________________________________________________________
lstm_3 (LSTM)                (None, 120, 100)          80400
_________________________________________________________________
batch_normalization_2 (Batch (None, 120, 100)          400
_________________________________________________________________
lstm_4 (LSTM)                (None, 120, 80)           57920
_________________________________________________________________
batch_normalization_3 (Batch (None, 120, 80)           320
_________________________________________________________________
```

```
lstm_5 (LSTM)                (None, 60)                33840
_________________________________________________________________
batch_normalization_4 (Batch (None, 60)                240
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 61
=================================================================
Total params: 2,684,413
Trainable params: 2,683,733
Non-trainable params: 680
_________________________________________________________________
None
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/tensorfl
ow/python/ops/math_ops.py:3066: to_int32 (from tensorflow.python.ops.ma
th_ops) is deprecated and will be removed in a future version.
Instructions for updating:
Use tf.cast instead.
Train on 196880 samples, validate on 196881 samples
Epoch 1/10
196880/196880 [==============================] - 3164s 16ms/step - los
s: 0.4910 - acc: 0.8030 - val_loss: 0.4144 - val_acc: 0.8547
Epoch 2/10
196880/196880 [==============================] - 3130s 16ms/step - los
s: 0.4248 - acc: 0.8552 - val_loss: 0.4166 - val_acc: 0.8547
Epoch 3/10
196880/196880 [==============================] - 3172s 16ms/step - los
s: 0.4192 - acc: 0.8553 - val_loss: 0.4237 - val_acc: 0.8547
Epoch 4/10
196880/196880 [==============================] - 3161s 16ms/step - los
s: 0.3334 - acc: 0.8690 - val_loss: 0.2458 - val_acc: 0.8992
Epoch 5/10
196880/196880 [==============================] - 3140s 16ms/step - los
s: 0.2501 - acc: 0.8991 - val_loss: 0.2314 - val_acc: 0.9070
Epoch 6/10
196880/196880 [==============================] - 3148s 16ms/step - los
s: 0.2285 - acc: 0.9081 - val_loss: 0.2320 - val_acc: 0.9095
Epoch 7/10
196880/196880 [==============================] - 3145s 16ms/step - los
s: 0.2169 - acc: 0.9122 - val_loss: 0.2226 - val_acc: 0.9090
Epoch 8/10
```

```
196880/196880 [==============================] - 3144s 16ms/step - los
s: 0.2092 - acc: 0.9161 - val_loss: 0.2308 - val_acc: 0.9100
Epoch 9/10
196880/196880 [==============================] - 3182s 16ms/step - los
s: 0.2053 - acc: 0.9176 - val_loss: 0.2244 - val_acc: 0.9104
Epoch 10/10
196880/196880 [==============================] - 3178s 16ms/step - los
s: 0.1990 - acc: 0.9202 - val_loss: 0.2235 - val_acc: 0.9110
Train Accuracy 0.9202356765784659
test score : 0.2235467241037283
test Accuracy : 0.9109716021359054
```




```
Time taken to run this cell : 9:02:45.687949
```

In [0]:
```
print('Train loss',ty)
```

```
Train loss [0.49096747402106294, 0.4247921708370311, 0.419169231686152
3, 0.33343958246519, 0.2501070746763699, 0.2285251474087435, 0.21694653
656777207, 0.20923510087015956, 0.20528901007566835, 0.1989786412913544
5]
```

In [0]:
```
print('test score',test_score_lstm_5)
```

```
test score 0.2235467241037283
```

```
test score 0.22354672410372283
```

Observation

In [0]:
```
from prettytable import PrettyTable
models=['RNN With 1 LSTM Layer',
        'RNN With 2 LSTM Layer',
        'RNN With 4 LSTM Layer',
       'RNN With 5 LSTM Layer']
training_accuracy=[train_accuracy_lstm_1,train_accuracy_lstm_2,
                   train_accuracy_lstm_4,train_accuracy_lstm_5]
test_accuracy=[test_accuracy_lstm_1,test_accuracy_lstm_2,
               test_accuracy_lstm_4,test_accuracy_lstm_5]
INDEX = [1,2,3,4]
# Initializing prettytable
Model_Performance = PrettyTable()
# Adding columns
Model_Performance.add_column("INDEX.",INDEX)
Model_Performance.add_column("MODEL_NAME",models)
Model_Performance.add_column("TRAINING ACCURACY",training_accuracy)
Model_Performance.add_column("TESTING ACCURACY",test_accuracy)
#Model_Performance.add_column("TEST SCORE",test_score)

# Printing the Model_Performance
print(Model_Performance)
```

```
+--------+----------------------+-------------------+----------------
-+
| INDEX. |       MODEL_NAME     | TRAINING ACCURACY | TESTING ACCURACY
|
+--------+----------------------+-------------------+----------------
-+
|   1    | RNN With 1 LSTM Layer |       0.9423      |      0.9035
|
|   2    | RNN With 2 LSTM Layer |       0.9392      |      0.9087
|
|   3    | RNN With 4 LSTM Layer |      0.936954     |      0.9075
|
```

```
|   4    | RNN With 5 LSTM Layer |       0.9202      |      0.9108
|
+--------+-----------------------+-------------------+-----------------
-+
```