Assignment_14(Amazon_Food_Reviews_LSTM_model)

September 20, 2018

1 OBJECTIVE :- Built LSTM model on Amazon Fine Food Reviews

In [2]:
```
# Installing package
!pip install gensim

# Importing libraries
import warnings
warnings.filterwarnings("ignore")

import pandas as pd
import numpy as np
import nltk
import string
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns

from sklearn.feature_extraction.text import CountVectorizer
from nltk.stem.porter import PorterStemmer
import re
import string
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
import pickle
```

```
Requirement already satisfied: gensim in /usr/local/lib/python3.6/dist-packages (3.5.0)
Requirement already satisfied: six>=1.5.0 in /usr/local/lib/python3.6/dist-packages (from gensi
Requirement already satisfied: smart-open>=1.2.1 in /usr/local/lib/python3.6/dist-packages (fro
Requirement already satisfied: numpy>=1.11.3 in /usr/local/lib/python3.6/dist-packages (from ge
Requirement already satisfied: scipy>=0.18.1 in /usr/local/lib/python3.6/dist-packages (from ge
Requirement already satisfied: requests in /usr/local/lib/python3.6/dist-packages (from smart-o
Requirement already satisfied: boto>=2.32 in /usr/local/lib/python3.6/dist-packages (from smart
Requirement already satisfied: bz2file in /usr/local/lib/python3.6/dist-packages (from smart-op
```

```
Requirement already satisfied: boto3 in /usr/local/lib/python3.6/dist-packages (from smart-oper
Requirement already satisfied: urllib3<1.23,>=1.21.1 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: chardet<3.1.0,>=3.0.2 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: idna<2.7,>=2.5 in /usr/local/lib/python3.6/dist-packages (from r
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.6/dist-packages (fr
Requirement already satisfied: botocore<1.13.0,>=1.12.7 in /usr/local/lib/python3.6/dist-packag
Requirement already satisfied: s3transfer<0.2.0,>=0.1.10 in /usr/local/lib/python3.6/dist-packa
Requirement already satisfied: jmespath<1.0.0,>=0.7.1 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: python-dateutil<3.0.0,>=2.1; python_version >= "2.7" in /usr/loc
Requirement already satisfied: docutils>=0.10 in /usr/local/lib/python3.6/dist-packages (from b
```

1.1 Loading Data from Reviews.CSV file in Google Drive

In [0]:
```
# Install the PyDrive wrapper & import libraries.
!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
```

In [0]:
```
# Authenticate and create the PyDrive client.
auth.authenticate_user()
gauth = GoogleAuth()
gauth.credentials = GoogleCredentials.get_application_default()
drive = GoogleDrive(gauth)
```

In [0]:
```
# Downloading a file based on its file ID
#file_id = 'REPLACE_WITH_YOUR_FILE_ID'
#downloaded = drive.CreateFile({'id': file_id})
downloaded = drive.CreateFile({'id':'1pHPZn0WOyqUGfBTLSuBw1ggKe_DOaZdw'})
downloaded.GetContentFile('Reviews.CSV')

# Getting data into a dataframe
df = pd.read_csv('Reviews.CSV')
```

In [6]:
```
df.head()
```

Out[6]:
```
   Id   ProductId          UserId                      ProfileName  \
0   1  B001E4KFG0  A3SGXH7AUHU8GW                       delmartian
1   2  B00813GRG4  A1D87F6ZCVE5NK                           dll pa
2   3  B000LQOCH0   ABXLMWJIXXAIN  Natalia Corres "Natalia Corres"
3   4  B000UA0QIQ  A395BORC6FGVXV                             Karl
4   5  B006K2ZZ7K  A1UQRSCLF8GW1T    Michael D. Bigham "M. Wassir"

   HelpfulnessNumerator  HelpfulnessDenominator  Score        Time  \
0                     1                       1      5  1303862400
1                     0                       0      1  1346976000
2                     1                       1      4  1219017600
```

```
3                     3                       3      2  1307923200
4                     0                       0      5  1350777600

                 Summary                                             Text
0  Good Quality Dog Food  I have bought several of the Vitality canned d...
1      Not as Advertised  Product arrived labeled as Jumbo Salted Peanut...
2  "Delight" says it all  This is a confection that has been around a fe...
3         Cough Medicine  If you are looking for the secret ingredient i...
4            Great taffy  Great taffy at a great price.  There was a wid...
```

In [7]:

```python
# Eliminating neutral reviews i.e. those reviews with Score = 3
filtered_data = df[df['Score'] != 3]

# Converting Score variables to binary class variable (1-positive review and 0-negativ
# Give reviews with Score>3 a positive rating (1) , and reviews with a score<3 a negat
def polarity(x):
    if x < 3:
        return 0
    return 1

# Applying polarity function on Score column of filtered_data
filtered_data['Score'] = filtered_data['Score'].map(polarity)

print(filtered_data.shape)
filtered_data.head()
```

```
(525814, 10)
```

Out[7]:

```
   Id   ProductId          UserId                      ProfileName  \
0   1  B001E4KFG0  A3SGXH7AUHU8GW                       delmartian
1   2  B00813GRG4  A1D87F6ZCVE5NK                           dll pa
2   3  B000LQOCH0   ABXLMWJIXXAIN  Natalia Corres "Natalia Corres"
3   4  B000UA0QIQ  A395BORC6FGVXV                             Karl
4   5  B006K2ZZ7K  A1UQRSCLF8GW1T    Michael D. Bigham "M. Wassir"

   HelpfulnessNumerator  HelpfulnessDenominator  Score        Time  \
0                     1                       1      1  1303862400
1                     0                       0      0  1346976000
2                     1                       1      1  1219017600
3                     3                       3      0  1307923200
4                     0                       0      1  1350777600

                 Summary                                             Text
0  Good Quality Dog Food  I have bought several of the Vitality canned d...
1      Not as Advertised  Product arrived labeled as Jumbo Salted Peanut...
2  "Delight" says it all  This is a confection that has been around a fe...
3         Cough Medicine  If you are looking for the secret ingredient i...
4            Great taffy  Great taffy at a great price.  There was a wid...
```

NOTE :- In above table , in Score column 1 = positive review and 0 = negative review

1.2 Data Cleaning: Deduplication

In [8]:
```
#Sorting data according to ProductId in ascending order
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplace=Fals

#Deduplication of entries
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, keep=

# Removing rows where HelpfulnessNumerator is greater than HelpfulnessDenominator
final = final[final.HelpfulnessNumerator <= final.HelpfulnessDenominator]

print(final.shape)
final[30:50]
```

```
(364171, 10)
```

Out[8]:
```
            Id   ProductId          UserId  \
150500  150501  0006641040   AJ46FKXOVC7NR
150492  150493  0006641040   AMX0PJKV4PPNJ
150499  150500  0006641040  A1IJKK6Q1GTEAY
150498  150499  0006641040  A3E7R866M94L0C
515425  515426  141278509X   AB1A5EGHHVA9M
24750    24751  2734888454  A1C298ITT645B6
24749    24750  2734888454  A13ISQV0U9GZIC
308076  308077  2841233731  A3QD68O22M2XHQ
171160  171161  7310172001   AFXMWPNS1BLU4
171159  171160  7310172001   A74C7IARQEM1R
171143  171144  7310172001  A1V5MY8V9AWUQB
171142  171143  7310172001  A2SW060IW01VPX
171147  171148  7310172001  A3TFTWTG2CC1GA
171141  171142  7310172001  A2ZO1AYFVQYG44
171140  171141  7310172001   AZ40270J4JBZN
171139  171140  7310172001   ADXXVGRCGQQUO
171138  171139  7310172001  A13MS1JQG2ADOJ
171137  171138  7310172001  A13LAEOYTXA11B
171158  171159  7310172001  A16GY2RCF410DT
171144  171145  7310172001  A1L8DNQYY69L2Z

                                   ProfileName  \
150500                       Nicholas A Mesiano
150492                   E. R. Bird "Ramseelbird"
150499                               A Customer
150498                   L. Barker "simienwolf"
515425                                  CHelmic
24750                          Hugh G. Pritchard
```

```
24749                                                Sandikaye
308076                                                 LABRNTH
171160                                              H. Sandler
171159                                                 stucker
171143                        Cheryl Sapper "champagne girl"
171142                                                     Sam
171147                                             J. Umphress
171141                                  Cindy Rellie "Rellie"
171140  Zhinka Chunmee "gamer from way back in the 70's"
171139                                     Richard Pearlstein
171138                                              C. Perrone
171137                              Dita Vyslouzilova "dita"
171158                                                      LB
171144                                               R. Flores

        HelpfulnessNumerator  HelpfulnessDenominator  Score        Time  \
150500                     2                       2      1   940809600
150492                    71                      72      1  1096416000
150499                     2                       2      1  1009324800
150498                     2                       2      1  1065830400
515425                     1                       1      1  1332547200
24750                      0                       0      1  1195948800
24749                      1                       1      0  1192060800
308076                     0                       0      1  1345852800
171160                     0                       0      1  1229385600
171159                     0                       0      1  1230076800
171143                     0                       0      1  1244764800
171142                     0                       0      1  1252022400
171147                     0                       0      1  1240272000
171141                     0                       0      1  1254960000
171140                     0                       0      1  1264291200
171139                     0                       0      1  1264377600
171138                     0                       0      1  1265760000
171137                     0                       0      1  1269216000
171158                     0                       0      1  1231718400
171144                     0                       0      1  1243728000

                                                  Summary  \
150500  This whole series is great way to spend time w...
150492  Read it once. Read it twice. Reading Chicken S...
150499                                It Was a favorite!
150498                                 Can't explain why
515425                                The best drink mix
24750                                 Dog Lover Delites
24749                                     made in china
308076               Great recipe book for my babycook
171160                                  Excellent treats
171159                                   Sophie's Treats
```

```
171143                        THE BEST healthy dog treat!
171142                   My Alaskan Malamute Loves Them!!
171147                                   Best treat ever!
171141      my 12 year old maltese has always loved these
171140                  Dogs, Cats, Ferrets all love this
171139                                          5 snouts!
171138                                Best dog treat ever
171137                          Great for puppy training
171158                                             Great!
171144                                   Terrific Treats

                                                     Text
150500  I can remember seeing the show when it aired o...
150492  These days, when a person says, "chicken soup"...
150499  This was a favorite book of mine when I was a ...
150498  This book has been a favorite of mine since I ...
515425  This product by Archer Farms is the best drink...
24750   Our dogs just love them.  I saw them in a pet ...
24749   My dogs loves this chicken but its a product f...
308076  This book is easy to read and the ingredients ...
171160  I have been feeding my greyhounds these treats...
171159  This is one product that my welsh terrier can ...
171143  This is the ONLY dog treat that my Lhasa Apso ...
171142  These liver treas are phenomenal. When i recei...
171147  This was the only treat my dog liked during ob...
171141  No waste , even if she is having a  day when s...
171140  I wanted a treat that was accepted and well li...
171139  My Westie loves these things!  She loves anyth...
171138  This is the only dog treat that my terrier wil...
171137  New puppy loves this, only treat he will pay a...
171158  My dog loves these treats!  We started using t...
171144  This is a great treat which all three of my do...
```

OBSERVATION :- Here books with ProductId - 0006641040 and 2841233731 are also there so we have to remove all these rows with these ProductIds from the data

In [9]:
```python
final = final[final['ProductId'] != '2841233731']
final = final[final['ProductId'] != '0006641040']
final.shape
```

Out[9]:
```
(364136, 10)
```

1.3 Text Preprocessing: Stemming, stop-word removal and Lemmatization.ű

In [10]:
```python
# Downloading stopwords
nltk.download('stopwords')

#set of stopwords in English
from nltk.corpus import stopwords
```

```
stop = set(stopwords.words('english'))
words_to_keep = set(('not'))
stop -= words_to_keep
#initialising the snowball stemmer
sno = nltk.stem.SnowballStemmer('english')

 #function to clean the word of any html-tags
def cleanhtml(sentence):
    cleanr = re.compile('<.*?>')
    cleantext = re.sub(cleanr, ' ', sentence)
    return cleantext

#function to clean the word of any punctuation or special characters
def cleanpunc(sentence):
    cleaned = re.sub(r'[?|!|\'|"|#]',r'',sentence)
    cleaned = re.sub(r'[.|,|)|(|\|/]',r' ',cleaned)
    return  cleaned
```

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

In [0]:
```
#Code for removing HTML tags , punctuations . Code for removing stopwords . Code for c
# also greater than 2 . Code for stemmimg and also to convert them to lowercase letter
i=0
str1=' '
final_string=[]
all_positive_words=[] # store words from +ve reviews here
all_negative_words=[] # store words from -ve reviews here.
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 descri
                    if(final['Score'].values)[i] == 0:
                        all_negative_words.append(s) #list of all words used to descri
                else:
                    continue
            else:
                continue
```

```
        str1 = b" ".join(filtered_sentence) #final string of cleaned words


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

```
In [12]: #adding a column of CleanedText which displays the data after pre-processing of the r
         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 (364136, 11)
```

```
Out[12]:              Id   ProductId          UserId        ProfileName  \
         515425  515426  141278509X   AB1A5EGHHVA9M            CHelmic
         24750    24751  2734888454  A1C298ITT645B6  Hugh G. Pritchard
         24749    24750  2734888454  A13ISQV0U9GZIC          Sandikaye
         171160  171161  7310172001   AFXMWPNS1BLU4         H. Sandler
         171159  171160  7310172001   A74C7IARQEM1R            stucker

                 HelpfulnessNumerator  HelpfulnessDenominator  Score        Time  \
         515425                     1                       1      1  1332547200
         24750                      0                       0      1  1195948800
         24749                      1                       1      0  1192060800
         171160                     0                       0      1  1229385600
         171159                     0                       0      1  1230076800

                             Summary                                               Text  \
         515425  The best drink mix  This product by Archer Farms is the best drink...
         24750    Dog Lover Delites  Our dogs just love them.  I saw them in a pet ...
         24749        made in china  My dogs loves this chicken but its a product f...
         171160    Excellent treats  I have been feeding my greyhounds these treats...
         171159     Sophie's Treats  This is one product that my welsh terrier can ...

                                                       CleanedText
         515425  product archer farm best drink mix ever mix fl...
         24750   dog love saw pet store tag attach regard made ...
         24749   dog love chicken product china wont buy anymor...
         171160  feed greyhound treat year hound littl finicki ...
         171159  one product welsh terrier eat sophi food alerg...
```

1.4 Converting this data as IMDB dataset

```
In [13]: ##Sorting data according to Time in ascending order for Time Based Splitting
         time_sorted_data = final.sort_values('Time', axis=0, ascending=True, inplace=False, k
```

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

# Finding all words in the vocabulary
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 :  71611
```

In [0]:
```python
# Storing all words in the dictionary (words as keys and index as values)
corpus = dict()
ind = 0
for sent in x:
  for word in sent.split():
    corpus.setdefault(word,[])
    corpus[word].append(ind)
    ind += 1

# Getting frequency for each word of vocabulary and storing it in a list
freq = []
for w in vocabulary:
  freq.append(len(corpus[w]))
```

In [0]:
```python
# Getting Index for each word in the vocabulary
# Sorting frequencies in decreasing order
inc_index =np.argsort(np.array(freq))[::-1]

# Allocating ranks to words of vocabulary in decreasing order of frequency and storing
word_rank = dict()
rank = 1
for i in inc_index:
  word_rank[vocabulary[i]] = rank
  rank +=1
```

In [0]:
```python
# Converting full data into imdb format
data = []
for sent in x:
  row = []
  for word in sent.split():
    if(len(word)>1):
      row.append(word_rank[word])
  data.append(row)

# Splitting the data into 50-50 train_data and test_data
```

```
from sklearn.model_selection import train_test_split
X_train, X_test, Y_train, Y_test = train_test_split(data, y, test_size=0.5, random_sta
```

In [17]:
```
print("No. of datapoints in X_train :",len(X_train))
print("No. of datapoints in X_test :",len(X_test))
print("Shape of Y_train :",Y_train.shape)
print("Shape of Y_test :",Y_test.shape)
```

```
No. of datapoints in X_train : 182068
No. of datapoints in X_test : 182068
Shape of Y_train : (182068,)
Shape of Y_test : (182068,)
```

In [18]:
```
# 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 [19]:
```
# truncate and/or pad input sequences
max_review_length = 100
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])
```

```
(182068, 100)
[  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 152
  30 241  93 877 313 117  14 329  47  67]
```

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()
```

1.5 (1) RNN with 1 LSTM layer

In [22]:
```
# create the model
embedding_vecor_length = 32

# Initialising the model
model_1 = Sequential()

# Adding embedding
model_1.add(Embedding(len(vocabulary), embedding_vecor_length, input_length=max_revie

# Adding Dropout
model_1.add(Dropout(0.2))

# Adding first LSTM layer
model_1.add(LSTM(100))

# Adding Dropout
model_1.add(Dropout(0.2))

# Adding output layer
model_1.add(Dense(1, activation='sigmoid'))

# Printing the model summary
print(model_1.summary())

# Compiling the model
model_1.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])

# Fitting the data to the model
history_1 = model_1.fit(X_train, Y_train, nb_epoch=10, batch_size=512 ,verbose=1,valid
```

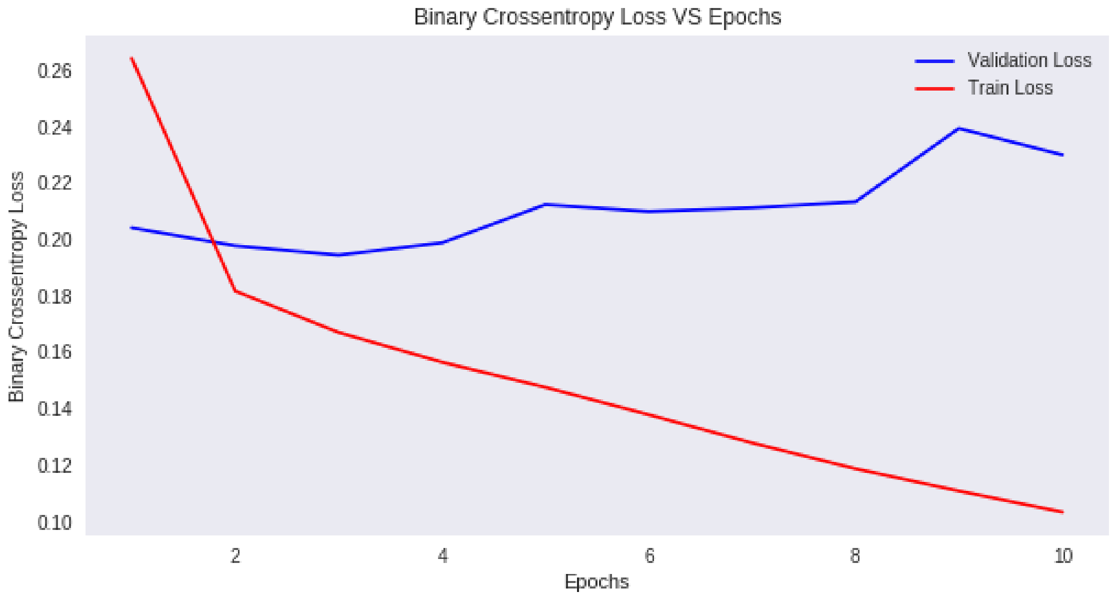
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_2 (Embedding)      (None, 100, 32)           2291552
_________________________________________________________________
dropout_3 (Dropout)          (None, 100, 32)           0
_________________________________________________________________
lstm_2 (LSTM)                (None, 100)               53200
_________________________________________________________________
```

```
dropout_4 (Dropout)          (None, 100)              0
_________________________________________________________________
dense_2 (Dense)              (None, 1)                101
=================================================================
Total params: 2,344,853
Trainable params: 2,344,853
Non-trainable params: 0
_________________________________________________________________
None
Train on 182068 samples, validate on 182068 samples
Epoch 1/10
182068/182068 [==============================] - 105s 577us/step - loss: 0.2643 - acc: 0.8981 -
Epoch 2/10
182068/182068 [==============================] - 104s 574us/step - loss: 0.1818 - acc: 0.9295 -
Epoch 3/10
182068/182068 [==============================] - 104s 574us/step - loss: 0.1671 - acc: 0.9357 -
Epoch 4/10
182068/182068 [==============================] - 103s 567us/step - loss: 0.1565 - acc: 0.9399 -
Epoch 5/10
182068/182068 [==============================] - 103s 564us/step - loss: 0.1477 - acc: 0.9433 -
Epoch 6/10
182068/182068 [==============================] - 103s 563us/step - loss: 0.1379 - acc: 0.9473 -
Epoch 7/10
182068/182068 [==============================] - 103s 564us/step - loss: 0.1279 - acc: 0.9516 -
Epoch 8/10
182068/182068 [==============================] - 102s 562us/step - loss: 0.1188 - acc: 0.9550 -
Epoch 9/10
182068/182068 [==============================] - 102s 563us/step - loss: 0.1109 - acc: 0.9582 -
Epoch 10/10
182068/182068 [==============================] - 103s 564us/step - loss: 0.1034 - acc: 0.9613 -
```

In [23]:
```
# Final evaluation of the model
scores = model_1.evaluate(X_test, Y_test, verbose=0)
print("Accuracy: %.2f%%" % (scores[1]*100))

# Test and train accuracy of the model
model_1_test = scores[1]
model_1_train = max(history_1.history['acc'])

# Plotting Train and Test Loss VS no. of epochs
# list of epoch numbers
x = list(range(1,11))

# Validation loss
vy = history_1.history['val_loss']
# Training loss
ty = history_1.history['loss']
```

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

```
Accuracy: 91.93%
```



1.6 (2). RNN with 2 LSTM layers

In [24]:
```
# create the model
embedding_vecor_length = 32

# Initialising the model
model_2 = Sequential()

# Adding embedding
model_2.add(Embedding(len(vocabulary), embedding_vecor_length, input_length=max_reviev

# Adding first LSTM layer
model_2.add(LSTM(100,return_sequences=True, dropout=0.4, recurrent_dropout=0.4))

# Adding second LSTM layer
model_2.add(LSTM(100, dropout=0.4, recurrent_dropout=0.4))

# Adding output layer
model_2.add(Dense(1, activation='sigmoid'))
```

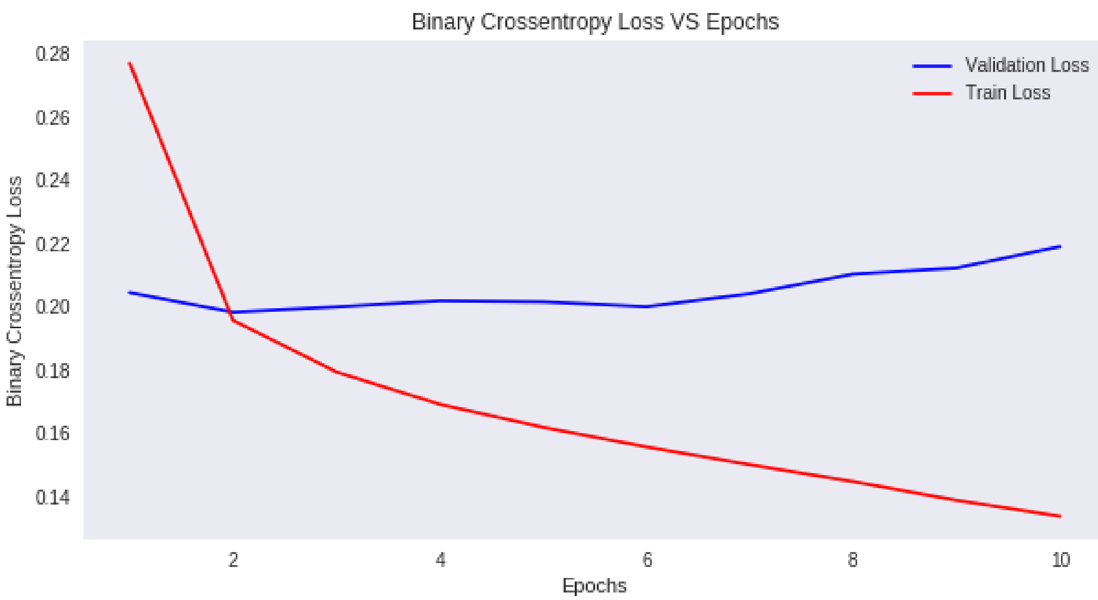
```
# Printing the model summary
print(model_2.summary())

# Compiling the model
model_2.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])

# Fitting the data to the model
history_2 = model_2.fit(X_train, Y_train, nb_epoch=10, batch_size=512 ,verbose=1,vali
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_3 (Embedding)      (None, 100, 32)           2291552
_________________________________________________________________
lstm_3 (LSTM)                (None, 100, 100)          53200
_________________________________________________________________
lstm_4 (LSTM)                (None, 100)               80400
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 101
=================================================================
Total params: 2,425,253
Trainable params: 2,425,253
Non-trainable params: 0
_________________________________________________________________
None
Train on 182068 samples, validate on 182068 samples
Epoch 1/10
182068/182068 [==============================] - 241s 1ms/step - loss: 0.2771 - acc: 0.8941 - v
Epoch 2/10
182068/182068 [==============================] - 239s 1ms/step - loss: 0.1958 - acc: 0.9242 - v
Epoch 3/10
182068/182068 [==============================] - 237s 1ms/step - loss: 0.1795 - acc: 0.9313 - v
Epoch 4/10
182068/182068 [==============================] - 236s 1ms/step - loss: 0.1693 - acc: 0.9354 - v
Epoch 5/10
182068/182068 [==============================] - 237s 1ms/step - loss: 0.1620 - acc: 0.9380 - v
Epoch 6/10
182068/182068 [==============================] - 237s 1ms/step - loss: 0.1558 - acc: 0.9403 - v
Epoch 7/10
182068/182068 [==============================] - 234s 1ms/step - loss: 0.1502 - acc: 0.9430 - v
Epoch 8/10
182068/182068 [==============================] - 241s 1ms/step - loss: 0.1448 - acc: 0.9449 - v
Epoch 9/10
182068/182068 [==============================] - 239s 1ms/step - loss: 0.1389 - acc: 0.9477 - v
Epoch 10/10
182068/182068 [==============================] - 238s 1ms/step - loss: 0.1338 - acc: 0.9493 - v
```

```
In [25]: # Final evaluation of the model
```

```
scores = model_2.evaluate(X_test, Y_test, verbose=0)
print("Accuracy: %.2f%%" % (scores[1]*100))

# Test and train accuracy of the model
model_2_test = scores[1]
model_2_train = max(history_2.history['acc'])

# Plotting Train and Test Loss VS no. of epochs
# list of epoch numbers
x = list(range(1,11))

# Validation loss
vy = history_2.history['val_loss']
# Training loss
ty = history_2.history['loss']

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

```
Accuracy: 91.97%
```



1.7 (3). RNN with 3 LSTM layers

```
In [27]: # create the model
         embedding_vecor_length = 32
```

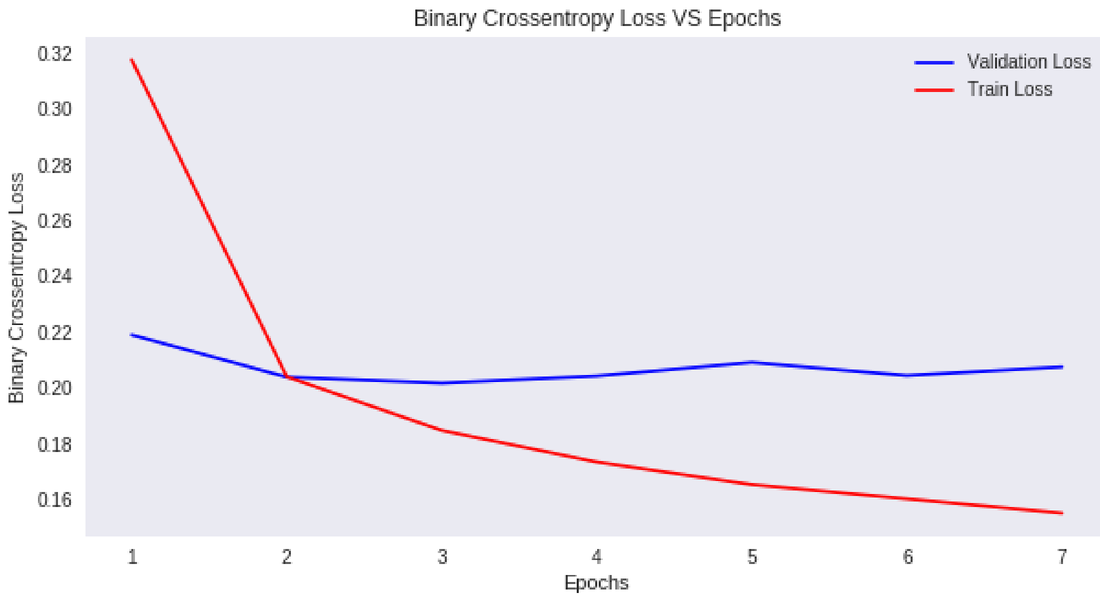
```
# Initialising the model
model_3 = Sequential()

# Adding embedding
model_3.add(Embedding(len(vocabulary), embedding_vecor_length, input_length=max_revie

# Adding first LSTM layer
model_3.add(LSTM(100,return_sequences=True, dropout=0.4, recurrent_dropout=0.4))

# Adding second LSTM layer
model_3.add(LSTM(100,return_sequences=True, dropout=0.5, recurrent_dropout=0.5))

# Adding third LSTM layer
model_3.add(LSTM(100, dropout=0.4, recurrent_dropout=0.4))

# Adding output layer
model_3.add(Dense(1, activation='sigmoid'))

# Printing the model summary
print(model_3.summary())

# Compiling the model
model_3.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])

# Fitting the data to the model
history_3 = model_3.fit(X_train, Y_train, nb_epoch=7, batch_size=1024 ,verbose=1,vali
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_5 (Embedding)      (None, 100, 32)           2291552
_________________________________________________________________
lstm_8 (LSTM)                (None, 100, 100)          53200
_________________________________________________________________
lstm_9 (LSTM)                (None, 100, 100)          80400
_________________________________________________________________
lstm_10 (LSTM)               (None, 100)               80400
_________________________________________________________________
dense_5 (Dense)              (None, 1)                 101
=================================================================
Total params: 2,505,653
Trainable params: 2,505,653
Non-trainable params: 0
_________________________________________________________________
None
Train on 182068 samples, validate on 182068 samples
Epoch 1/7
182068/182068 [==============================] - 195s 1ms/step - loss: 0.3176 - acc: 0.8799 - v
```

```
Epoch 2/7
182068/182068 [==============================] - 190s 1ms/step - loss: 0.2041 - acc: 0.9215 - v
Epoch 3/7
182068/182068 [==============================] - 190s 1ms/step - loss: 0.1849 - acc: 0.9294 - v
Epoch 4/7
182068/182068 [==============================] - 190s 1ms/step - loss: 0.1736 - acc: 0.9344 - v
Epoch 5/7
182068/182068 [==============================] - 190s 1ms/step - loss: 0.1655 - acc: 0.9377 - v
Epoch 6/7
182068/182068 [==============================] - 190s 1ms/step - loss: 0.1604 - acc: 0.9399 - v
Epoch 7/7
182068/182068 [==============================] - 190s 1ms/step - loss: 0.1552 - acc: 0.9419 - v
```

In [28]:
```
# Final evaluation of the model
scores = model_3.evaluate(X_test, Y_test, 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_3.history['acc'])

# Plotting Train and Test Loss VS no. of epochs
# list of epoch numbers
x = list(range(1,8))

# Validation loss
vy = history_3.history['val_loss']
# Training loss
ty = history_3.history['loss']

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

```
Accuracy: 92.17%
```



1.8 (4). RNN with 4 LSTM layers

In [30]:
```
# create the model
embedding_vecor_length = 64

# Initialising the model
model_4 = Sequential()

# Adding embedding
model_4.add(Embedding(len(vocabulary), embedding_vecor_length, input_length=max_review

# Adding first LSTM layer
model_4.add(LSTM(120,return_sequences=True, dropout=0.6, recurrent_dropout=0.6))

# Adding second LSTM layer
model_4.add(LSTM(100,return_sequences=True, dropout=0.5, recurrent_dropout=0.5))

# Adding third LSTM layer
model_4.add(LSTM(80,return_sequences=True, dropout=0.4, recurrent_dropout=0.4))

# Adding fourth LSTM layer
model_4.add(LSTM(60, dropout=0.3, recurrent_dropout=0.3))

# Adding output layer
model_4.add(Dense(1, activation='sigmoid'))
```

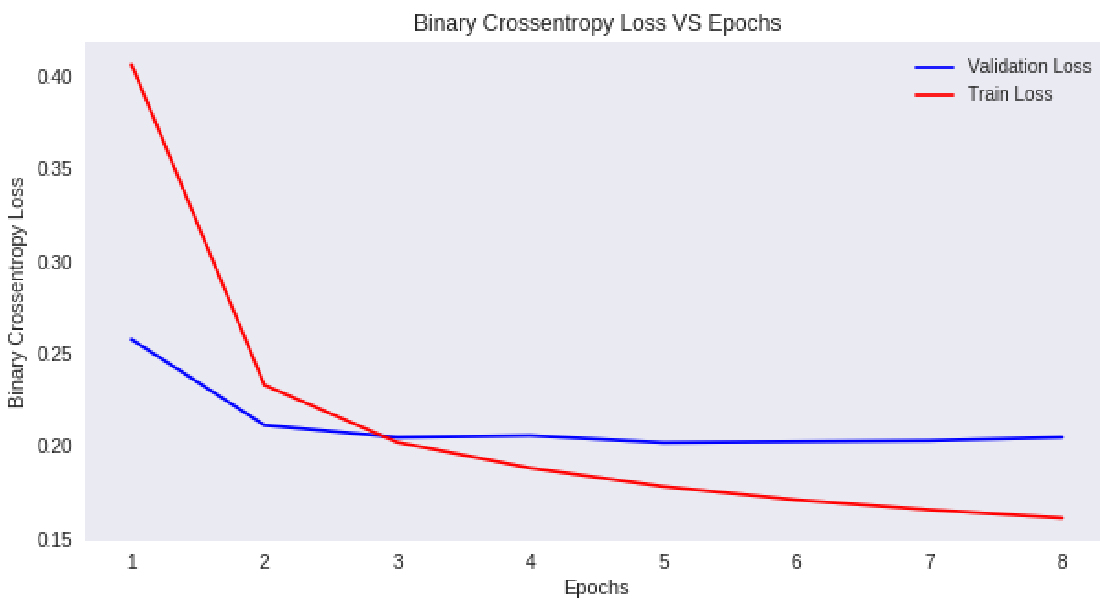
```
# Printing the model summary
print(model_4.summary())

# Compiling the model
model_4.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])

# Fitting the data to the model
history_4 = model_4.fit(X_train, Y_train, nb_epoch=8, batch_size=2048 ,verbose=1,vali
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_7 (Embedding)      (None, 100, 64)           4583104
_________________________________________________________________
lstm_15 (LSTM)               (None, 100, 120)          88800
_________________________________________________________________
lstm_16 (LSTM)               (None, 100, 100)          88400
_________________________________________________________________
lstm_17 (LSTM)               (None, 100, 80)           57920
_________________________________________________________________
lstm_18 (LSTM)               (None, 60)                33840
_________________________________________________________________
dense_7 (Dense)              (None, 1)                 61
=================================================================
Total params: 4,852,125
Trainable params: 4,852,125
Non-trainable params: 0
_________________________________________________________________
None
Train on 182068 samples, validate on 182068 samples
Epoch 1/8
182068/182068 [==============================] - 183s 1ms/step - loss: 0.4062 - acc: 0.8517 - v
Epoch 2/8
182068/182068 [==============================] - 178s 976us/step - loss: 0.2331 - acc: 0.9087 -
Epoch 3/8
182068/182068 [==============================] - 177s 971us/step - loss: 0.2022 - acc: 0.9222 -
Epoch 4/8
182068/182068 [==============================] - 177s 972us/step - loss: 0.1883 - acc: 0.9281 -
Epoch 5/8
182068/182068 [==============================] - 177s 971us/step - loss: 0.1783 - acc: 0.9320 -
Epoch 6/8
182068/182068 [==============================] - 177s 972us/step - loss: 0.1711 - acc: 0.9349 -
Epoch 7/8
182068/182068 [==============================] - 177s 972us/step - loss: 0.1658 - acc: 0.9372 -
Epoch 8/8
182068/182068 [==============================] - 177s 972us/step - loss: 0.1614 - acc: 0.9392 -
```

In [31]:
```
# Final evaluation of the model
```

```
scores = model_4.evaluate(X_test, Y_test, verbose=0)
print("Accuracy: %.2f%%" % (scores[1]*100))

# Test and train accuracy of the model
model_4_test = scores[1]
model_4_train = max(history_4.history['acc'])

# Plotting Train and Test Loss VS no. of epochs
# list of epoch numbers
x = list(range(1,9))

# Validation loss
vy = history_4.history['val_loss']
# Training loss
ty = history_4.history['loss']

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

```
Accuracy: 92.18%
```



1.9 CONCLUSION

1.10 (a). Procedure Followed :

1. Load Amazon Fine Food Reviews dataset

2. Perform text pre-processing
3. Sort the dataset on the basis of time and after that find vocabulary for all the reviews in the dataset
4. Now compute frequencies for each word of vocabulary
5. Index each word in the decreasing order of frequencies (Word with max frequency will have rank 1 or index 1)
6. Convert the dataset into imdb dataset format
7. Split whole dataset into 50-50 for training_data and test_data randomly
8. Now pad or truncate each review intpo sequences of length 100
9. Now implement RNN with 1 , 2 ,3 and 4 LSTM layers
10. Find accuracy for each
11. Draw Binary Crossentropy Loss VS No.of Epochs plot

1.11 (b) Table (Different models with their train and test accuracies):

In [33]:
```
# Installing the library prettytable
!pip install prettytable

# Creating table using PrettyTable library
from prettytable import PrettyTable

# Names of models
names = ['RNN With 1 LSTM Layer','RNN With 2 LSTM Layers','RNN With 3 LSTM Layers','RI

# Training accuracies
train_acc = [model_1_train,model_2_train,model_3_train,model_4_train]

# Test accuracies
test_acc = [model_1_test,model_2_test,model_3_test,model_4_test]

numbering = [1,2,3,4]

# Initializing prettytable
ptable = PrettyTable()

# Adding columns
ptable.add_column("S.NO.",numbering)
ptable.add_column("MODEL",names)
ptable.add_column("Training Accuracy",train_acc)
ptable.add_column("Test Accuracy",test_acc)

# Printing the Table
print(ptable)
```

```
Requirement already satisfied: prettytable in /usr/local/lib/python3.6/dist-packages (0.7.2)
+-------+------------------------+--------------------+--------------------+
| S.NO. |         MODEL          | Training Accuracy  |   Test Accuracy    |
+-------+------------------------+--------------------+--------------------+
```

1	RNN With 1 LSTM Layer	0.9612836961699912	0.919315860009658
2	RNN With 2 LSTM Layers	0.9493485950435232	0.9196618845705999
3	RNN With 3 LSTM Layers	0.9418843509005513	0.9217160621306325
4	RNN With 4 LSTM Layers	0.9391600942390127	0.921792956479109