Amazon Fine Food Reviews Analysis

Data Source: https://www.kaggle.com/snap/amazon-fine-food-reviews

EDA: https://nycdatascience.com/blog/student-works/amazon-fine-foods-visualization/

The Amazon Fine Food Reviews dataset consists of reviews of fine foods from Amazon.

Number of reviews: 568,454
Number of users: 256,059
Number of products: 74,258
Timespan: Oct 1999 - Oct 2012
Number of Attributes/Columns in data: 10

Attribute Information:

1. Id
2. ProductId - unique identifier for the product
3. UserId - unqiue identifier for the user
4. ProfileName
5. HelpfulnessNumerator - number of users who found the review helpful
6. HelpfulnessDenominator - number of users who indicated whether they found the review helpful or not
7. Score - rating between 1 and 5
8. Time - timestamp for the review
9. Summary - brief summary of the review
10. Text - text of the review

Objective:

Given a review, determine whether the review is positive (rating of 4 or 5) or negative (rating of 1 or 2).

[Q] How to determine if a review is positive or negative?

[Ans] We could use Score/Rating. A rating of 4 or 5 can be cosnidered as a positive review. A rating of 1 or 2 can be considered as negative one. A review of rating 3 is considered nuetral and such reviews are ignored from our analysis. This is an approximate and proxy way of determining the polarity (positivity/negativity) of a review.

[1]. Reading Data

[1.1] Loading the data

The dataset is available in two forms

1. .csv file
2. SQLite Database

In order to load the data, We have used the SQLITE dataset as it is easier to query the data and visualise the data efficiently.

Here as we only want to get the global sentiment of the recommendations (positive or negative), we will purposefully ignore all Scores equal to 3. If the score is above 3, then the recommendation wil be set to "positive". Otherwise, it will be set to "negative".

In [1]:
```
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")


import sqlite3
import pandas as pd
import numpy as np
import nltk
import string
```

```
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer

from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics import confusion_matrix
from sklearn import metrics
from sklearn.metrics import roc_curve, auc
from nltk.stem.porter import PorterStemmer

import re
# Tutorial about Python regular expressions: https://pymotw.com/2/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

from tqdm import tqdm
import os
```

In [2]:

```
# using SQLite Table to read data.
con = sqlite3.connect('database.sqlite')

# filtering only positive and negative reviews i.e.
# not taking into consideration those reviews with Score=3
# SELECT * FROM Reviews WHERE Score != 3 LIMIT 500000, will give top 50
0000 data points
# you can change the number to any other number based on your computing
 power

# filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Sco
re != 3 LIMIT 500000""", con)
# for tsne assignment you can take 5k data points
```

```
filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score
 != 3 LIMIT 200000""", con)

# Give reviews with Score>3 a positive rating(1), and reviews with a sc
ore<3 a negative rating(0).
def partition(x):
    if x < 3:
        return 0
    return 1

#changing reviews with score less than 3 to be positive and vice-versa
actualScore = filtered_data['Score']
positiveNegative = actualScore.map(partition)
filtered_data['Score'] = positiveNegative
print("Number of data points in our data", filtered_data.shape)
filtered_data.head(3)
```

```
Number of data points in our data (200000, 10)
```

Out[2]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenomin
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	
2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	

In [3]:
```
display = pd.read_sql_query("""
SELECT UserId, ProductId, ProfileName, Time, Score, Text, COUNT(*)
FROM Reviews
GROUP BY UserId
HAVING COUNT(*)>1
""", con)
```

In [4]:
```
print(display.shape)
display.head()
```

```
(80668, 7)
```

Out[4]:

	UserId	ProductId	ProfileName	Time	Score	Text	COUNT(*)
0	#oc-R115TNMSPFT9I7	B005ZBZLT4	Breyton	1331510400	2	Overall its just OK when considering the price...	2
1	#oc-R11D9D7SHXIJB9	B005HG9ESG	Louis E. Emory "hoppy"	1342396800	5	My wife has recurring extreme muscle spasms, u...	3
2	#oc-R11DNU2NBKQ23Z	B005ZBZLT4	Kim Cieszykowski	1348531200	1	This coffee is horrible and unfortunately not ...	2
3	#oc-R11O5J5ZVQE25C	B005HG9ESG	Penguin Chick	1346889600	5	This will be the bottle that you grab from the...	3
4	#oc-R12KPBODL2B5ZD	B007OSBEV0	Christopher P. Presta	1348617600	1	I didnt like this coffee. Instead of telling y...	2

In [5]:
```
display[display['UserId']=='AZY10LLTJ71NX']
```

Out[5]:

	UserId	ProductId	ProfileName	Time	Score	Text	COUNT(*)
80638	AZY10LLTJ71NX	B001ATMQK2	undertheshrine "undertheshrine"	1296691200	5	I bought this 6 pack because for the price tha...	5

In [6]:
```
display['COUNT(*)'].sum()
```

Out[6]: 393063

[2] Exploratory Data Analysis

[2.1] Data Cleaning: Deduplication

It is observed (as shown in the table below) that the reviews data had many duplicate entries. Hence it was necessary to remove duplicates in order to get unbiased results for the analysis of the data. Following is an example:

In [7]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND UserId="AR5J8UI46CURR"
ORDER BY ProductID
""", con)
display.head()
```

Out[7]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenon

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenon
0	78445	B000HDL1RQ	AR5J8UI46CURR	Geetha Krishnan	2	
1	138317	B000HDOPYC	AR5J8UI46CURR	Geetha Krishnan	2	
2	138277	B000HDOPYM	AR5J8UI46CURR	Geetha Krishnan	2	
3	73791	B000HDOPZG	AR5J8UI46CURR	Geetha Krishnan	2	
4	155049	B000PAQ75C	AR5J8UI46CURR	Geetha Krishnan	2	

As it can be seen above that same user has multiple reviews with same values for HelpfulnessNumerator, HelpfulnessDenominator, Score, Time, Summary and Text and on doing analysis it was found that

ProductId=B000HDOPZG was Loacker Quadratini Vanilla Wafer Cookies, 8.82-Ounce Packages (Pack of 8)

ProductId=B000HDL1RQ was Loacker Quadratini Lemon Wafer Cookies, 8.82-Ounce Packages (Pack of 8) and so on

It was inferred after analysis that reviews with same parameters other than ProductId belonged to the same product just having different flavour or quantity. Hence in order to reduce redundancy it was decided to eliminate the rows having same parameters.

The method used for the same was that we first sort the data according to ProductId and then just keep the first similar product review and delelte the others. for eg. in the above just the review for ProductId=B000HDL1RQ remains. This method ensures that there is only one representative for each product and deduplication without sorting would lead to possibility of different representatives still existing for the same product.

In [8]:
```
#Sorting data according to ProductId in ascending order
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplace=False, kind='quicksort', na_position='last')
```

In [9]:
```
#Deduplication of entries
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, keep='first', inplace=False)
final.shape
```

Out[9]:
```
(160178, 10)
```

In [10]:
```
#Checking to see how much % of data still remains
(final['Id'].size*1.0)/(filtered_data['Id'].size*1.0)*100
```

Out[10]:
```
80.089
```

Observation:- It was also seen that in two rows given below the value of HelpfulnessNumerator is greater than HelpfulnessDenominator which is not practically possible hence these two rows too are removed from calcualtions

In [11]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND Id=44737 OR Id=64422
ORDER BY ProductID
""", con)
```

```
display.head()
```

Out[11]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenom
0	64422	B000MIDROQ	A161DK06JJMCYF	J. E. Stephens "Jeanne"	3	
1	44737	B001EQ55RW	A2V0I904FH7ABY	Ram	3	

In [12]:

```
final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
```

In [13]:

```
#Before starting the next phase of preprocessing lets see the number of
 entries left
print(final.shape)

#How many positive and negative reviews are present in our dataset?
final['Score'].value_counts()
```

```
(160176, 10)
```

Out[13]:

```
1    134799
0     25377
Name: Score, dtype: int64
```

[3] Preprocessing

[3.1]. Preprocessing Review Text

Now that we have finished deduplication our data requires some preprocessing before we go on further with analysis and making the prediction model.

Hence in the Preprocessing phase we do the following in the order below:-

1. Begin by removing the html tags
2. Remove any punctuations or limited set of special characters like , or . or # etc.
3. Check if the word is made up of english letters and is not alpha-numeric
4. Check to see if the length of the word is greater than 2 (as it was researched that there is no adjective in 2-letters)
5. Convert the word to lowercase
6. Remove Stopwords
7. Finally Snowball Stemming the word (it was obsereved to be better than Porter Stemming)

After which we collect the words used to describe positive and negative reviews

In [14]:

```
# printing some random reviews
sent_0 = final['Text'].values[0]
print(sent_0)
print("="*50)

sent_1000 = final['Text'].values[1000]
print(sent_1000)
print("="*50)

sent_1500 = final['Text'].values[1500]
print(sent_1500)
print("="*50)

sent_4900 = final['Text'].values[4900]
print(sent_4900)
print("="*50)
```

```
I remembered this book from my childhood and got it for my kids.  It's
just as good as I remembered and my kids love it too.  My older daughte
r now reads it to her sister.  Good rhymes and nice pictures.
```

```
==================================================
The qualitys not as good as the lamb and rice but it didn't seem to bot
her his stomach, you get 10 more pounds and it is cheaper wich is a plu
s for me. You can always ad your own rice and veggies. Its fresher that
way and better for him in my opinion. Plus if you you can get it delive
rd to your house for free its even better.  Gotta love pitbulls
==================================================
This is the Japanese version of breadcrumb (pan=bread, a Portuguese loa
n-word, and&quot;ko-&quot;  is &quot;child of&quot; or of &quot;derived
from&quot;.) Panko are used for katsudon, tonkatsu or cutlets served on
rice or in soups. The cutlets, pounded chicken or pork, are coated with
these light and crispy crumbs and fried. They are not gritty and dense
like regular crumbs. They are very nice on deep fried shrimps and decor
ative for a more gourmet touch.
==================================================
What can I say... If Douwe Egberts was good enough for my dutch grandmo
ther, it's perfect for me.  I like this flavor best with my Senseo... I
t has a nice dark full body flavor without the burt bean taste I tend s
ense with starbucks.  It's a shame most americans haven't bought into s
ingle serve coffe makers as our Dutch counter parts have.  Every cup is
fresh brewed and doesn't sit long enough on my desk to get that old tas
te either.
==================================================
```

In [15]:

```
# remove urls from text python: https://stackoverflow.com/a/40823105/40
84039
sent_0 = re.sub(r"http\S+", "", sent_0)
sent_1000 = re.sub(r"http\S+", "", sent_1000)
sent_150 = re.sub(r"http\S+", "", sent_1500)
sent_4900 = re.sub(r"http\S+", "", sent_4900)

print(sent_0)
```

```
I remembered this book from my childhood and got it for my kids.  It's
just as good as I remembered and my kids love it too.  My older daughte
r now reads it to her sister.  Good rhymes and nice pictures.
```

In [16]:

```
# https://stackoverflow.com/questions/16206380/python-beautifulsoup-how
-to-remove-all-tags-from-an-element
```

```python
from bs4 import BeautifulSoup

soup = BeautifulSoup(sent_0, 'lxml')
text = soup.get_text()
print(text)
print("="*50)

soup = BeautifulSoup(sent_1000, 'lxml')
text = soup.get_text()
print(text)
print("="*50)

soup = BeautifulSoup(sent_1500, 'lxml')
text = soup.get_text()
print(text)
print("="*50)

soup = BeautifulSoup(sent_4900, 'lxml')
text = soup.get_text()
print(text)
```

```
I remembered this book from my childhood and got it for my kids.  It's
just as good as I remembered and my kids love it too.  My older daughte
r now reads it to her sister.  Good rhymes and nice pictures.
==================================================
The qualitys not as good as the lamb and rice but it didn't seem to bot
her his stomach, you get 10 more pounds and it is cheaper wich is a plu
s for me. You can always ad your own rice and veggies. Its fresher that
way and better for him in my opinion. Plus if you you can get it delive
rd to your house for free its even better.  Gotta love pitbulls
==================================================
This is the Japanese version of breadcrumb (pan=bread, a Portuguese loa
n-word, and"ko-"  is "child of" or of "derived from".) Panko are used f
or katsudon, tonkatsu or cutlets served on rice or in soups. The cutlet
s, pounded chicken or pork, are coated with these light and crispy crum
bs and fried. They are not gritty and dense like regular crumbs. They a
re very nice on deep fried shrimps and decorative for a more gourmet to
uch.
==================================================
What can I say... If Douwe Egberts was good enough for my dutch grandmo
```

```
ther, it's perfect for me.  I like this flavor best with my Senseo... I
t has a nice dark full body flavor without the burt bean taste I tend s
ense with starbucks.  It's a shame most americans haven't bought into s
ingle serve coffe makers as our Dutch counter parts have.  Every cup is
fresh brewed and doesn't sit long enough on my desk to get that old tas
te either.
```

In [17]:

```python
# https://stackoverflow.com/a/47091490/4084039
import re

def decontracted(phrase):
    # specific
    phrase = re.sub(r"won't", "will not", phrase)
    phrase = re.sub(r"can\'t", "can not", phrase)

    # general
    phrase = re.sub(r"n\'t", " not", phrase)
    phrase = re.sub(r"\'re", " are", phrase)
    phrase = re.sub(r"\'s", " is", phrase)
    phrase = re.sub(r"\'d", " would", phrase)
    phrase = re.sub(r"\'ll", " will", phrase)
    phrase = re.sub(r"\'t", " not", phrase)
    phrase = re.sub(r"\'ve", " have", phrase)
    phrase = re.sub(r"\'m", " am", phrase)
    return phrase
```

In [18]:

```python
sent_1500 = decontracted(sent_1500)
print(sent_1500)
print("="*50)
```

```
This is the Japanese version of breadcrumb (pan=bread, a Portuguese loa
n-word, and&quot;ko-&quot;  is &quot;child of&quot; or of &quot;derived
from&quot;.) Panko are used for katsudon, tonkatsu or cutlets served on
rice or in soups. The cutlets, pounded chicken or pork, are coated with
these light and crispy crumbs and fried. They are not gritty and dense
like regular crumbs. They are very nice on deep fried shrimps and decor
ative for a more gourmet touch.
==================================================
```

In [19]:
```
#remove words with numbers python: https://stackoverflow.com/a/1808237
0/4084039
sent_0 = re.sub("\S*\d\S*", "", sent_0).strip()
print(sent_0)
```

```
I remembered this book from my childhood and got it for my kids.  It's
just as good as I remembered and my kids love it too.  My older daughte
r now reads it to her sister.  Good rhymes and nice pictures.
```

In [20]:
```
#remove spacial character: https://stackoverflow.com/a/5843547/4084039
sent_1500 = re.sub('[^A-Za-z0-9]+', ' ', sent_1500)
print(sent_1500)
```

```
This is the Japanese version of breadcrumb pan bread a Portuguese loan
word and quot ko quot is quot child of quot or of quot derived from quo
t Panko are used for katsudon tonkatsu or cutlets served on rice or in
soups The cutlets pounded chicken or pork are coated with these light a
nd crispy crumbs and fried They are not gritty and dense like regular c
rumbs They are very nice on deep fried shrimps and decorative for a mor
e gourmet touch
```

In [21]:
```
# https://gist.github.com/sebleier/554280
# we are removing the words from the stop words list: 'no', 'nor', 'no
t'
# <br /><br /> ==> after the above steps, we are getting "br br"
# we are including them into stop words list
# instead of <br /> if we have <br/> these tags would have revmoved in
 the 1st step

stopwords= set(['br', 'the', 'i', 'me', 'my', 'myself', 'we', 'our', 'o
urs', 'ourselves', 'you', "you're", "you've",\
            "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselve
s', 'he', 'him', 'his', 'himself', \
            'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'it
s', 'itself', 'they', 'them', 'their',\
            'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'th
is', 'that', "that'll", 'these', 'those', \
            'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'h
```

```
ave', 'has', 'had', 'having', 'do', 'does', \
            'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or',
 'because', 'as', 'until', 'while', 'of', \
            'at', 'by', 'for', 'with', 'about', 'against', 'between',
'into', 'through', 'during', 'before', 'after',\
            'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out',
'on', 'off', 'over', 'under', 'again', 'further',\
            'then', 'once', 'here', 'there', 'when', 'where', 'why', 'h
ow', 'all', 'any', 'both', 'each', 'few', 'more',\
            'most', 'other', 'some', 'such', 'only', 'own', 'same', 's
o', 'than', 'too', 'very', \
            's', 't', 'can', 'will', 'just', 'don', "don't", 'should',
"should've", 'now', 'd', 'll', 'm', 'o', 're', \
            've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't",
'didn', "didn't", 'doesn', "doesn't", 'hadn',\
            "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "is
n't", 'ma', 'mightn', "mightn't", 'mustn',\
            "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn',
 "shouldn't", 'wasn', "wasn't", 'weren', "weren't", \
            'won', "won't", 'wouldn', "wouldn't"])
```

In [22]:

```
# Combining all the above stundents
from tqdm import tqdm
preprocessed_reviews = []
# tqdm is for printing the status bar
for sentance in tqdm(final['Text'].values):
    sentance = re.sub(r"http\S+", "", sentance)
    sentance = BeautifulSoup(sentance, 'lxml').get_text()
    sentance = decontracted(sentance)
    sentance = re.sub("\S*\d\S*", "", sentance).strip()
    sentance = re.sub('[^A-Za-z]+', ' ', sentance)
    # https://gist.github.com/sebleier/554280
    sentance = ' '.join(e.lower() for e in sentance.split() if e.lower
() not in stopwords)
    preprocessed_reviews.append(sentance.strip())
```

```
100%|██████████| 160176/160176 [01:11<00:00, 2225.79it/s]
```

In [23]:

```
preprocessed_reviews[1500]
```

Out[23]: 'japanese version breadcrumb pan bread portuguese loan word ko child derived panko used katsudon tonkatsu cutlets served rice soups cutlets pounded chicken pork coated light crispy crumbs fried not gritty dense like regular crumbs nice deep fried shrimps decorative gourmet touch'

[3.2] Obtaining the Required DataFrame

In [24]:
```
type(preprocessed_reviews)
```

Out[24]: list

In [25]:
```
print(final.shape)
```

(160176, 10)

We obtain a list at the end of all the Preprocessing whereas the data frame that we obtained at the end was named 'final'. Initially I considered 200K datapoints to work upon which got reduced to approx. 160K datapoints after all the text processing and data deduplication.

In [26]:
```
final['Preprocessed_Reviews'] = preprocessed_reviews
```

Basically I have taken the entire list and added the list as a column to the entire dataframe, such that each value corresponds to a row in the dataframe.

In [27]:
```
final.head()
```

Out[27]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessI
138695	150513	0006641040	ASH0DZQQF6AIZ	tessarat	0	

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessI
138707	150525	0006641040	A2QID6VCFTY51R	Rick	1	
138708	150526	0006641040	A3E9QZFE9KXH8J	R. Mitchell	11	
138686	150504	0006641040	AQEYF1AXARWJZ	Les Sinclair "book maven"	1	
138685	150503	0006641040	A3R5XMPFU8YZ4D	Her Royal Motherliness "Nana"	1	

Now I have a total of approx. 160K rows in the dataframe called 'final', of which I will consider only 100K rows to be applied to the Logistic Regression Classifier. Also here you have the Unix Timestamp in the data, which is basically the time when the review was posted.

This makes it possible to carry out Time Based Split of the data instead of random splitting of the data into Train, CV and Test Datasets. For Time Based Split I will take the oldest of the reviews as the Training Data, the intermediate reviews as the CV data and the latest reviews as the Test data.

In [28]:

```
final_TBS = final.sort_values('Time')
final_TBS.head()
```

Out[28]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfulnes
138706	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0	
138683	150501	0006641040	AJ46FKXOVC7NR	Nicholas A Mesiano	2	
70688	76882	B00002N8SM	A32DW342WBJ6BX	Buttersugar	0	
1146	1245	B00002Z754	A29Z5PI9BW2PU3	Robbie	7	
1145	1244	B00002Z754	A3B8RCEI0FXFI6	B G Chase	10	

Now the values are sorted on the basis of Time. We know that by default the values are sorted in ascending order.

First I will remove all the useless columns from my dataframe. The only columns that we are concerned about here in this case are the 'Score' & 'Preprocessed_Reviews' (Without carrying out any Feature Engineering). Remaining columns in the dataframe are of no use to us.

In [29]:
```
df = final_TBS[['Score','Preprocessed_Reviews']]
df.head()
```

Out[29]:

	Score	Preprocessed_Reviews
138706	1	witty little book makes son laugh loud recite ...
138683	1	remember seeing show aired television years ag...
70688	1	bought apartment infested fruit flies hours tr...
1146	1	really good idea final product outstanding use...
1145	1	received shipment could hardly wait try produc...

In [30]:
```
#considering only the top 100K rows in our dataset
cleandf = df[:100000]

#separately obtaining the 'reviews' as well as the corresponding 'scor
e' class labels
reviews_column = cleandf['Preprocessed_Reviews']
score_column = cleandf['Score']

#obtaining indices for each row in the dataframe. Will be used for join
ing later
indices = []
for i in range(cleandf.shape[0]):
    indices.append(i)

original_df = pd.DataFrame({'ID': indices, 'Preprocessed_Reviews':revie
ws_column, 'Score':score_column})
original_df.head()
```

Out[30]:

	ID	Preprocessed_Reviews	Score
138706	0	witty little book makes son laugh loud recite ...	1
138683	1	remember seeing show aired television years ag...	1
70688	2	bought apartment infested fruit flies hours tr...	1
1146	3	really good idea final product outstanding use...	1

1146	5	really good idea final product outstanding use...	1

	ID	Preprocessed_Reviews	Score
1145	4	received shipment could hardly wait try produc...	1

[4] Data Preperation in the Required Format for LSTM

- While we are carrying out the Data Preperation, what we need to consider to start with, is to obtain each review as an element in a list. **This is a step that is needed to be carried out in order to obtain the entire Vocabulary.**
- This is followed by splitting each word in each review as a string instead of taking the entire review list element into consideration, after which we use Counter to count the frequency of occurence of each word in the Vocabulary.
- Now we carry out a ranking of these words such that the ranking of the most occuring word in our vocabulary is 1, followed by the next most occuring word and so on. ***This ranking for each word is what is going to be used as an encoding mechanism for each word.***

[4.1] Data Preperation for Sentiment Classification

In [31]:

```
#obtaining each row in the 'reviews_column' separately as a part of a l
ist
all_reviews = []
for i in reviews_column:
    all_reviews.append(i)

print(all_reviews[1])
print("="*100)
print ('Number of reviews :', len(all_reviews))
```

```
remember seeing show aired television years ago child sister later boug
ht lp day thirty something used series books songs student teaching pre
schoolers turned whole school purchasing cd along books children tradit
ion lives
```

ion tives

==
Number of reviews : 100000

Obtaining list of Tuples denoting the Count of Occurence for each word in the Vocabulary :-

In [32]:
```
#Refer: https://towardsdatascience.com/sentiment-analysis-using-lstm-st
ep-by-step-50d074f09948

#obtaining the frequencies for each word in the vocabulary
import collections
from collections import Counter

base_string = ''
all_words = base_string.join(all_reviews)
word_list = all_words.split()

word_count = Counter(word_list)
total_words = len(word_list)
sorted_words = word_count.most_common()

#printing the top 50 words and their corresponding frequencies
print(sorted_words[:50])
```

```
[('not', 100009), ('like', 40249), ('good', 31372), ('one', 28723), ('t
aste', 27696), ('great', 26345), ('would', 25806), ('coffee', 23691),
('flavor', 22874), ('product', 21825), ('tea', 21688), ('no', 18291),
('food', 18075), ('get', 17933), ('love', 15650), ('amazon', 15571),
('really', 15539), ('much', 15141), ('also', 14587), ('use', 13940),
('time', 13786), ('little', 13677), ('find', 13300), ('make', 12902),
('even', 12890), ('best', 12294), ('price', 11980), ('chocolate', 1189
3), ('well', 11601), ('buy', 11376), ('better', 11339), ('tried', 1129
8), ('eat', 11045), ('try', 10725), ('sugar', 10242), ('could', 9622),
('dog', 9177), ('found', 9061), ('free', 9052), ('first', 8803), ('ba
g', 8772), ('water', 8621), ('sweet', 8597), ('made', 8550), ('cup', 85
```

```
07), ('used', 8364), ('box', 8067), ('way', 8026), ('two', 7984), ('dri
nk', 7930)]
```

Obtaining Encoding for each word in the Vocabulary basis the Frequency Ranking:-

In [33]:

```
# Refer : https://stackoverflow.com/questions/7971618/python-return-fir
st-n-keyvalue-pairs-from-dict
from itertools import islice

def take(n, iterable):
    "Return first n items of the iterable as a list"
    return list(islice(iterable, n))

#Ranking each word in the vocabulary basis its frequency of occurence
vocab_to_int = {word:i+1 for i, (word,cnt) in enumerate(sorted_words)}
sample_vocab_to_int = take(50,vocab_to_int.items())
print(sample_vocab_to_int)
```

```
[('not', 1), ('like', 2), ('good', 3), ('one', 4), ('taste', 5), ('grea
t', 6), ('would', 7), ('coffee', 8), ('flavor', 9), ('product', 10),
('tea', 11), ('no', 12), ('food', 13), ('get', 14), ('love', 15), ('ama
zon', 16), ('really', 17), ('much', 18), ('also', 19), ('use', 20), ('t
ime', 21), ('little', 22), ('find', 23), ('make', 24), ('even', 25),
('best', 26), ('price', 27), ('chocolate', 28), ('well', 29), ('buy', 3
0), ('better', 31), ('tried', 32), ('eat', 33), ('try', 34), ('sugar',
35), ('could', 36), ('dog', 37), ('found', 38), ('free', 39), ('first',
40), ('bag', 41), ('water', 42), ('sweet', 43), ('made', 44), ('cup', 4
5), ('used', 46), ('box', 47), ('way', 48), ('two', 49), ('drink', 50)]
```

In [34]:

```
#encoding each word in each review basis its ranking
reviews_int = []
for review in all_reviews:
    encoding = [vocab_to_int.get(w) for w in review.split()]
    reviews_int.append(encoding)
print(reviews_int[0:3])
```

```
[[17870, 22, 1333, 69, 349, 5006, 4182, 28456, 1197, 3165, 501, 86, 581
6, 10677, 1256, 40974, 2150, 17871, 3811, 15, 142, 1805, 1333, 16313, 2
```

```
8457, 1420, 1333, 1773, 2254, 349, 58, 227, 28456, 3423, 2088], [655, 1
816, 1347, 23063, 9149, 71, 272, 957, 1388, 528, 78, 28458, 54, 4183, 7
5, 46, 4567, 2955, 11085, 3656, 7352, 15100, 745, 103, 985, 719, 7075,
501, 2955, 823, 3717, 2045], [78, 4110, 8301, 144, 3970, 461, 1161, 614
4, 59, 3970, 547, 221, 2457, 543, 171, 1, 112, 2474, 1906, 3970, 3165,
779, 924, 152, 4, 2436, 3186, 1062, 34, 798, 7063]]
```

Obtaining Dataframe with ID Column as Primary Key and Encoding for each word:-

In [35]:

```
encoded_df = pd.DataFrame({'ID':indices,'Encoded_value': reviews_int})
encoded_df.head()
```

Out[35]:

	ID	Encoded_value
0	0	[17870, 22, 1333, 69, 349, 5006, 4182, 28456, ...
1	1	[655, 1816, 1347, 23063, 9149, 71, 272, 957, 1...
2	2	[78, 4110, 8301, 144, 3970, 461, 1161, 6144, 5...
3	3	[17, 3, 527, 2320, 10, 1478, 20, 19925, 1197, ...
4	4	[288, 747, 36, 1483, 594, 34, 10, 15, 40978, 7...

Combining both of the Dataframes on the ID Column for Visual Purposes:-

In [36]:

```
combined_df = original_df.merge(encoded_df, on='ID',how='left')
final_df = combined_df[['ID','Preprocessed_Reviews','Encoded_value','Sc
ore']]
final_df.head()
```

Out[36]:

	ID	Preprocessed_Reviews	Encoded_value	Score
0	0	witty little book makes son laugh loud recite ...	[17870, 22, 1333, 69, 349, 5006, 4182, 28456, ...	1
1	1	remember seeing show aired television years ag...	[655, 1816, 1347, 23063, 9149, 71, 272, 957, 1...	1

	ID	Preprocessed_Reviews	Encoded_value	Score
2	2	bought apartment infested fruit flies hours tr...	[78, 4110, 8301, 144, 3970, 461, 1161, 6144, 5...	1
3	3	really good idea final product outstanding use...	[17, 3, 527, 2320, 10, 1478, 20, 19925, 1197, ...	1
4	4	received shipment could hardly wait try produc...	[288, 747, 36, 1483, 594, 34, 10, 15, 40978, 7...	1

[4.2] Obtaining Train & Test Datasets

In [37]:

```
#Splitting the Train and Test Datasets in the 80:20 ratio
X_Train = final_df['Encoded_value'][:int(final_df.shape[0]*0.8)]
Y_Train = final_df['Score'][:int(final_df.shape[0]*0.8)]

X_Test = final_df['Encoded_value'][int(final_df.shape[0]*0.8):final_df.
shape[0]]
Y_Test = final_df['Score'][int(final_df.shape[0]*0.8):final_df.shape[0
]]
```

In [38]:

```
print(X_Train[1])
print(type(X_Train[1]))
print(len(X_Train[1]))
```

```
[655, 1816, 1347, 23063, 9149, 71, 272, 957, 1388, 528, 78, 28458, 54,
4183, 75, 46, 4567, 2955, 11085, 3656, 7352, 15100, 745, 103, 985, 719,
7075, 501, 2955, 823, 3717, 2045]
<class 'list'>
32
```

[5] Building LSTM Models

In [39]:

```
# LSTM for sequence classification in the Amazon Fine Food Reviews data
```

```
set
import numpy
import keras
from keras import optimizers
from keras import metrics
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.normalization import BatchNormalization
from keras.layers import Dropout
from keras.layers import Bidirectional

# fix random seed for reproducibility
numpy.random.seed(7)
```

```
Using TensorFlow backend.
```

Handling 'None' Values in the Encoding:-

In [40]:

```
lists_with_None = []
with_None=[]
for k in range(len(X_Train)):
    b = all(isinstance(x, int) for x in X_Train[k])
    if b is not True:
        lists_with_None.append(k)
        with_None.append(X_Train[k])

X_Train_final=[]
for k in X_Train:
    X_Train_final.append(list(filter(None,k)))

X_Test_final=[]
for k in X_Test:
    X_Test_final.append(list(filter(None,k)))
```

Padding the Input Sentences to fix the Input Size:-

In [41]:
```
# truncate and/or pad input sequences
max_review_length = 500

X_Train_final = sequence.pad_sequences(X_Train_final, maxlen=max_review
_length)
X_Test_final = sequence.pad_sequences(X_Test_final, maxlen=max_review_l
ength)

print(X_Train.shape)
print(X_Train[1])
```

```
(80000,)
[655, 1816, 1347, 23063, 9149, 71, 272, 957, 1388, 528, 78, 28458, 54,
4183, 75, 46, 4567, 2955, 11085, 3656, 7352, 15100, 745, 103, 985, 719,
7075, 501, 2955, 823, 3717, 2045]
```

[5.1] Model 1 : Single LSTM Layer

[5.1.1] Constructing the Neural Network

In [42]:
```
# Creating the model
#Refer: https://datascience.stackexchange.com/questions/10615/number-of
-parameters-in-an-lstm-model

top_words = 132432
embedding_vector_length = 32

model1 = Sequential()
model1.add(Embedding(top_words+1, embedding_vector_length, input_length
=max_review_length))
model1.add(LSTM(100))

model1.add(Dense(1, activation='sigmoid'))
print(model1.summary())
```

```
Model: "sequential_1"
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
embedding_1 (Embedding)      (None, 500, 32)           4237856   
_________________________________________________________________
lstm_1 (LSTM)                (None, 100)               53200     
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 101       
=================================================================
Total params: 4,291,157
Trainable params: 4,291,157
Non-trainable params: 0
_________________________________________________________________
None
```

[5.1.2] Running the Model on Train & Test Datasets for 10 Epochs

In [45]:

```
batch_size= 64
epochs=10

model1.compile(loss='binary_crossentropy', optimizer=optimizers.Adam(lr
=0.001), metrics=[keras.metrics.AUC(),

                  'accuracy'])
M1_history = model1.fit(X_Train_final, Y_Train, batch_size=batch_size,
epochs=epochs, verbose=1,
                        validation_data=(X_Test_final, Y_Test))
```

```
Train on 80000 samples, validate on 20000 samples
Epoch 1/10
80000/80000 [==============================] - 952s 12ms/step - loss:
0.2294 - auc_1: 0.9164 - accuracy: 0.9122 - val_loss: 0.2084 - val_auc_
1: 0.9472 - val_accuracy: 0.9159
Epoch 2/10
80000/80000 [==============================] - 929s 12ms/step - loss:
0.1494 - auc_1: 0.9665 - accuracy: 0.9440 - val_loss: 0.2069 - val_auc_
1: 0.9475 - val_accuracy: 0.9179
```

```
Epoch 3/10
80000/80000 [==============================] - 936s 12ms/step - loss:
0.1164 - auc_1: 0.9789 - accuracy: 0.9577 - val_loss: 0.2198 - val_auc_
1: 0.9438 - val_accuracy: 0.9178
Epoch 4/10
80000/80000 [==============================] - 942s 12ms/step - loss:
0.0915 - auc_1: 0.9860 - accuracy: 0.9679 - val_loss: 0.2324 - val_auc_
1: 0.9390 - val_accuracy: 0.9101
Epoch 5/10
80000/80000 [==============================] - 942s 12ms/step - loss:
0.0699 - auc_1: 0.9914 - accuracy: 0.9760 - val_loss: 0.3401 - val_auc_
1: 0.9094 - val_accuracy: 0.9063
Epoch 6/10
80000/80000 [==============================] - 959s 12ms/step - loss:
0.0543 - auc_1: 0.9938 - accuracy: 0.9824 - val_loss: 0.3138 - val_auc_
1: 0.9130 - val_accuracy: 0.9114
Epoch 7/10
80000/80000 [==============================] - 928s 12ms/step - loss:
0.0430 - auc_1: 0.9959 - accuracy: 0.9853 - val_loss: 0.3716 - val_auc_
1: 0.9000 - val_accuracy: 0.9087
Epoch 8/10
80000/80000 [==============================] - 856s 11ms/step - loss:
0.0315 - auc_1: 0.9970 - accuracy: 0.9900 - val_loss: 0.4110 - val_auc_
1: 0.8860 - val_accuracy: 0.9032
Epoch 9/10
80000/80000 [==============================] - 847s 11ms/step - loss:
0.0263 - auc_1: 0.9979 - accuracy: 0.9915 - val_loss: 0.4214 - val_auc_
1: 0.8913 - val_accuracy: 0.9054
Epoch 10/10
80000/80000 [==============================] - 848s 11ms/step - loss:
0.0207 - auc_1: 0.9983 - accuracy: 0.9935 - val_loss: 0.4552 - val_auc_
1: 0.8913 - val_accuracy: 0.9032
```

Function to obtain the Training & Test AUC Values against the Number of Epochs

In [43]:

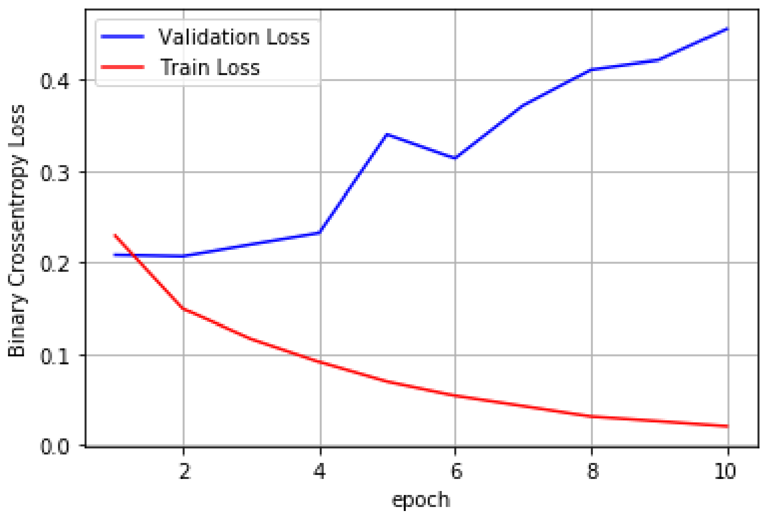
```
def plt_dynamic(x, vy, ty, ax, colors=['b']):
    ax.plot(x, vy, 'b', label="Validation Loss")
    ax.plot(x, ty, 'r', label="Train Loss")
```

```
    plt.legend()
    plt.grid()
    fig.canvas.draw()
```

[5.1.3] Number of Epochs vs Train AUC & Test AUC

In [50]:
```
score1 = model1.evaluate(X_Test_final, Y_Test, verbose=0)
print('Test loss:', score1[0])
print('Test auc value:', score1[1])
print('Test accuracy:', score1[2])

fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch') ; ax.set_ylabel('Binary Crossentropy Loss')

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

# print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epo
chs=nb_epoch, verbose=1, validation_data=(X_test, Y_test))

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

# loss : training loss
# acc : train accuracy
# for each key in histrory.history we will have a list of length equal
 to number of epochs

vy = M1_history.history['val_loss']
ty = M1_history.history['loss']
plt_dynamic(x, vy, ty, ax)
```

```
Test loss: 0.45523406787402926
Test auc value: 0.8912628889083862
Test accuracy: 0.903249979019165
```



[5.2] Model 2 : Stacked LSTM Layers

[5.2.1] Constructing the Neural Network

In [44]:

```
model2 = Sequential()
model2.add(Embedding(top_words+1, embedding_vector_length, input_length
=max_review_length))
model2.add(LSTM(100, kernel_initializer='he_uniform', dropout=0.4, retu
rn_sequences=True))
model2.add(BatchNormalization())
model2.add(LSTM(100,kernel_initializer='he_uniform', dropout=0.4))
model2.add(BatchNormalization())

model2.add(Dense(1, activation='sigmoid'))
print(model2.summary())
```

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
```

```
Layer (type)                 Output Shape              Param #
=================================================================
embedding_2 (Embedding)      (None, 500, 32)           4237856
_________________________________________________________________
lstm_2 (LSTM)                (None, 500, 100)          53200
_________________________________________________________________
batch_normalization_1 (Batch (None, 500, 100)          400
_________________________________________________________________
lstm_3 (LSTM)                (None, 100)               80400
_________________________________________________________________
batch_normalization_2 (Batch (None, 100)               400
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 101
=================================================================
Total params: 4,372,357
Trainable params: 4,371,957
Non-trainable params: 400
_________________________________________________________________
None
```

[5.2.2] Running the Model on Train & Test Datasets for 10 Epochs

In [47]:

```
model2.compile(loss='binary_crossentropy', optimizer=optimizers.Adam(lr
=0.001), metrics=[keras.metrics.AUC(),

                  'accuracy'])
M2_history = model2.fit(X_Train_final, Y_Train, batch_size=batch_size,
epochs=epochs, verbose=1,
                        validation_data=(X_Test_final, Y_Test))
```

```
Train on 80000 samples, validate on 20000 samples
Epoch 1/10
80000/80000 [==============================] - 1793s 22ms/step - loss:
0.3111 - auc_1: 0.8472 - accuracy: 0.8698 - val_loss: 0.4087 - val_auc_
1: 0.9083 - val_accuracy: 0.8715
Epoch 2/10
80000/80000 [==============================] - 1780s 22ms/step - loss:
0.1921 - auc_1: 0.9437 - accuracy: 0.9259 - val_loss: 0.6663 - val_auc_
```

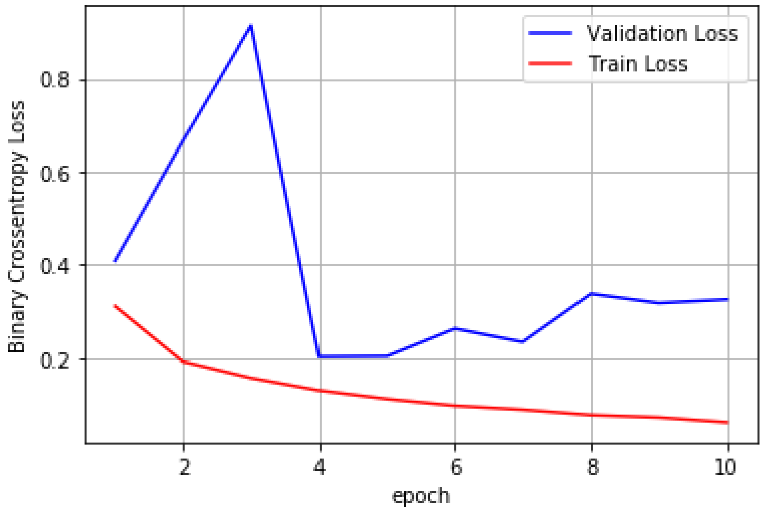
```
1: 0.8171 - val_accuracy: 0.8471
Epoch 3/10
80000/80000 [==============================] - 1789s 22ms/step - loss: 
0.1570 - auc_1: 0.9624 - accuracy: 0.9412 - val_loss: 0.9134 - val_auc_
1: 0.9313 - val_accuracy: 0.5107
Epoch 4/10
80000/80000 [==============================] - 1783s 22ms/step - loss: 
0.1304 - auc_1: 0.9737 - accuracy: 0.9524 - val_loss: 0.2030 - val_auc_
1: 0.9499 - val_accuracy: 0.9204
Epoch 5/10
80000/80000 [==============================] - 1785s 22ms/step - loss: 
0.1120 - auc_1: 0.9800 - accuracy: 0.9596 - val_loss: 0.2040 - val_auc_
1: 0.9484 - val_accuracy: 0.9176
Epoch 6/10
80000/80000 [==============================] - 1779s 22ms/step - loss: 
0.0975 - auc_1: 0.9842 - accuracy: 0.9650 - val_loss: 0.2630 - val_auc_
1: 0.9362 - val_accuracy: 0.9172
Epoch 7/10
80000/80000 [==============================] - 1857s 23ms/step - loss: 
0.0890 - auc_1: 0.9867 - accuracy: 0.9682 - val_loss: 0.2343 - val_auc_
1: 0.9439 - val_accuracy: 0.9112
Epoch 8/10
80000/80000 [==============================] - 1973s 25ms/step - loss: 
0.0774 - auc_1: 0.9903 - accuracy: 0.9719 - val_loss: 0.3376 - val_auc_
1: 0.9424 - val_accuracy: 0.8791
Epoch 9/10
80000/80000 [==============================] - 1911s 24ms/step - loss: 
0.0723 - auc_1: 0.9907 - accuracy: 0.9744 - val_loss: 0.3177 - val_auc_
1: 0.9150 - val_accuracy: 0.9132
Epoch 10/10
80000/80000 [==============================] - 1783s 22ms/step - loss: 
0.0617 - auc_1: 0.9930 - accuracy: 0.9784 - val_loss: 0.3254 - val_auc_
1: 0.9094 - val_accuracy: 0.9134
```

[5.2.3] Number of Epochs vs Train AUC & Test AUC

In [48]:
```
score2 = model2.evaluate(X_Test_final, Y_Test, verbose=0)
print('Test loss:', score2[0])
```

```
print('Test auc value:', score2[1])
print('Test accuracy:', score2[2])

fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch') ; ax.set_ylabel('Binary Crossentropy Loss')

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

# print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epo
chs=nb_epoch, verbose=1, validation_data=(X_test, Y_test))

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

# loss : training loss
# acc : train accuracy
# for each key in histrory.history we will have a list of length equal
 to number of epochs

vy = M2_history.history['val_loss']
ty = M2_history.history['loss']
plt_dynamic(x, vy, ty, ax)
```

```
Test loss: 0.32536794913969935
Test auc value: 0.9093945622444153
Test accuracy: 0.9133999943733215
```



[5.3] Model 3 : Stacked LSTM Layers with Bidirectional RNN

[5.3.1] Constructing the Neural Network

In [46]:
```
model3 = Sequential()
model3.add(Embedding(top_words+1, embedding_vector_length, input_length
=max_review_length))
model3.add(Bidirectional(LSTM(100, kernel_initializer='he_uniform', dro
pout=0.4, return_sequences=True)))
model3.add(BatchNormalization())
model3.add(Bidirectional(LSTM(100,kernel_initializer='he_uniform', drop
out=0.4)))
model3.add(BatchNormalization())

model3.add(Dense(1, activation='sigmoid'))
model3.summary()
```

```
Model: "sequential_4"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
embedding_4 (Embedding)      (None, 500, 32)           4237856   
_________________________________________________________________
bidirectional_1 (Bidirection (None, 500, 200)          106400    
_________________________________________________________________
batch_normalization_3 (Batch (None, 500, 200)          800       
_________________________________________________________________
bidirectional_2 (Bidirection (None, 200)               240800    
_________________________________________________________________
batch_normalization_4 (Batch (None, 200)               800       
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 201       
=================================================================
Total params: 4,586,857
Trainable params: 4,586,057
Non-trainable params: 800
_________________________________________________________________
```

[5.3.2] Running the Model on Train & Test Datasets for 10 Epochs

In [49]:
```
batch_size= 64
epochs=10

model3.compile(loss='binary_crossentropy', optimizer=optimizers.Adam(lr
=0.001), metrics=[keras.metrics.AUC(),

                  'accuracy'])
M3_history = model3.fit(X_Train_final, Y_Train, batch_size=batch_size,
epochs=epochs, verbose=1,
                        validation_data=(X_Test_final, Y_Test))
```

```
Train on 80000 samples, validate on 20000 samples
Epoch 1/10
80000/80000 [==============================] - 3365s 42ms/step - loss:
```

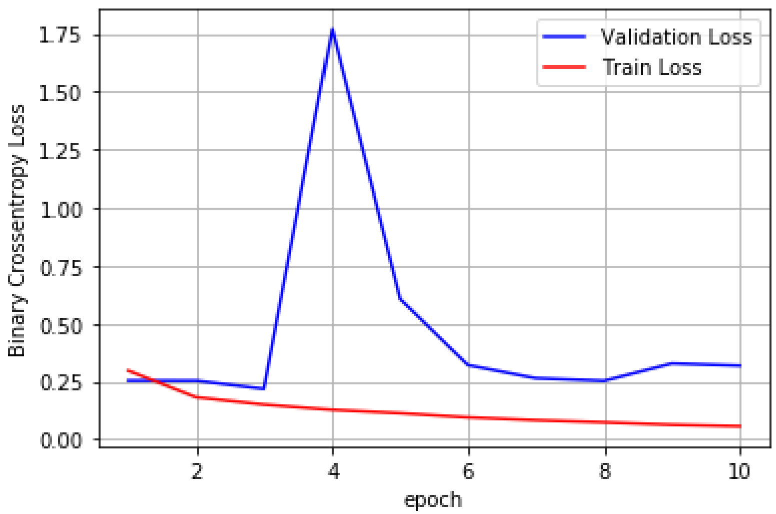
```
0.2965 - auc_1: 0.8613 - accuracy: 0.8766 - val_loss: 0.2535 - val_auc_
1: 0.9353 - val_accuracy: 0.9080
Epoch 2/10
80000/80000 [==============================] - 3599s 45ms/step - loss:
0.1814 - auc_1: 0.9498 - accuracy: 0.9305 - val_loss: 0.2530 - val_auc_
1: 0.9475 - val_accuracy: 0.8940
Epoch 3/10
80000/80000 [==============================] - 3514s 44ms/step - loss:
0.1497 - auc_1: 0.9659 - accuracy: 0.9448 - val_loss: 0.2178 - val_auc_
1: 0.9472 - val_accuracy: 0.9175
Epoch 4/10
80000/80000 [==============================] - 3371s 42ms/step - loss:
0.1268 - auc_1: 0.9748 - accuracy: 0.9534 - val_loss: 1.7704 - val_auc_
1: 0.8591 - val_accuracy: 0.1699
Epoch 5/10
80000/80000 [==============================] - 3531s 44ms/step - loss:
0.1124 - auc_1: 0.9803 - accuracy: 0.9593 - val_loss: 0.6061 - val_auc_
1: 0.9395 - val_accuracy: 0.7533
Epoch 6/10
80000/80000 [==============================] - 3659s 46ms/step - loss:
0.0941 - auc_1: 0.9853 - accuracy: 0.9657 - val_loss: 0.3207 - val_auc_
1: 0.9181 - val_accuracy: 0.8975
Epoch 7/10
80000/80000 [==============================] - 3662s 46ms/step - loss:
0.0819 - auc_1: 0.9882 - accuracy: 0.9719 - val_loss: 0.2639 - val_auc_
1: 0.9333 - val_accuracy: 0.9172
Epoch 8/10
80000/80000 [==============================] - 3656s 46ms/step - loss:
0.0726 - auc_1: 0.9905 - accuracy: 0.9745 - val_loss: 0.2526 - val_auc_
1: 0.9352 - val_accuracy: 0.9120
Epoch 9/10
80000/80000 [==============================] - 3649s 46ms/step - loss:
0.0622 - auc_1: 0.9926 - accuracy: 0.9785 - val_loss: 0.3275 - val_auc_
1: 0.9377 - val_accuracy: 0.8913
Epoch 10/10
80000/80000 [==============================] - 3647s 46ms/step - loss:
0.0557 - auc_1: 0.9940 - accuracy: 0.9805 - val_loss: 0.3181 - val_auc_
1: 0.9163 - val_accuracy: 0.9168
```

[5.3.3] Number of Epochs vs Train AUC & Validation AUC

In [50]:

```
score3 = model3.evaluate(X_Test_final, Y_Test, verbose=0)
print('Test loss:', score3[0])
print('Test auc value:', score3[1])
print('Test accuracy:', score3[2])

fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch') ; ax.set_ylabel('Binary Crossentropy Loss')

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

# print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epo
chs=nb_epoch, verbose=1, validation_data=(X_test, Y_test))

# we will get val_loss and val_acc only when you pass the parameter val
idation_data
# val_loss : validation loss
# val_acc : validation accuracy

# loss : training loss
# acc : train accuracy
# for each key in histrory.history we will have a list of length equal
 to number of epochs

vy = M3_history.history['val_loss']
ty = M3_history.history['loss']
plt_dynamic(x, vy, ty, ax)
```

```
Test loss: 0.3181260586164892
Test auc value: 0.9163286089897156
Test accuracy: 0.9167500138282776
```



[6] Conclusion

The Amazon Fine Food Reviews Dataset consists of Reviews and their corresponding polarities ie whether the review is positive or negative. We have already tried various Machine Learning models on the Amazon Fine Food Reviews Dataset, and now we will proceed with Deep Learning Modelling for the same.

LSTMs make sure that our Long Term Dependecies for the review polarities are taken care of. Also, LSTMs are a great idea to implement because LSTMs take into account the sequence information of the sentences, something that is very important but we have ignored so far in the Machine Learning Text Featurizations that we applied such as BOW, TFIDF, and Word2Vec. But in order to build the LSTM Models we need to first carry out Data Preparation in the format needed for LSTMs.

We are considering a total of 200K reviews to start with, because of computational limitations which after deduplication results in approximately 160K reviews. Out of these, we only consider 100K reviews where we split the early 80K Reviews (basis time) into the Train Data and the remaining 20K reviews as the Test Dataset {Our Metrics should improve even further if we increase our Train and Test Dataset Sizes}. First, we consider the entire vocabulary and then obtain the frequency of occurence for each word in the vocabulary, on the basis of which each word is ranked. This Ranking is what is used to encode the Reviews in the numerical format.

After this data preperation is completed, we build LSTM Models on top of it. First we build a single layer LSTM with 100 units (dimensionality of the output space) on top of which we measure the metrics of binary log loss, AUC Value as well as Accuracy. We give the highest preference for the Test AUC Values because Accuracy can be easily skewed in our case towards the majority class in our case : because our dataset is imbalanced. This is followed by Stacked LSTM with a total of 2 layers and then Bidirectional RNN. Again, we consider Adam as the optimizer for our task.

As expected from the results that are summarised below, the stacked Bidirectional RNN works very well and better than the other 2 models because it even takes into consideration the dependency of the words coming afterwards. The summary of each of the metrics obtained is as follows :

In [47]:
```
from prettytable import PrettyTable

x=PrettyTable()
x.field_names=["Model","Model Type","Test Log Loss","Test AUC","Test Ac
curacy"]

print ("Metrics for different LSTM Architectures after 10 Epochs:")
print("="*100)

x.add_row(["Model 1","Single layer LSTM", "0.455","0.891","90.32%"])
x.add_row(["Model 2","Stacked LSTM", "0.325","0.909","91.33%"])
x.add_row(["Model 3","Stacked Bidirectional RNN", "0.318","0.916","91.6
8%"])

print(x)
```

```
Metrics for different LSTM Architectures after 10 Epochs:
========================================================================
=============================
```

```
+---------+-------------------------+--------------+----------+-----
----------+
|  Model  |        Model Type       | Test Log Loss | Test AUC | Test
Accuracy |
+---------+-------------------------+--------------+----------+-----
----------+
| Model 1 |     Single layer LSTM     |     0.455     |  0.891   |
90.32%    |
| Model 2 |        Stacked LSTM       |     0.325     |  0.909   |
91.33%    |
| Model 3 | Stacked Bidirectional RNN |     0.318     |  0.916   |
91.68%    |
+---------+-------------------------+--------------+----------+-----
----------+
```