LSTM_AFFR

July 19, 2020

1 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.

2 [1]. Reading Data

2.1 [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".

[ ]:
```
%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 numpy import random
from sklearn.model_selection import train_test_split

from sklearn.preprocessing import StandardScaler

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

from bs4 import BeautifulSoup


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

from sklearn.metrics import roc_curve,accuracy_score
from sklearn.metrics import precision_score, recall_score
from sklearn.metrics import f1_score, confusion_matrix
```

[ ]:
```python
from google.colab import drive
drive.mount('/content/drive')
```

```
Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?client_id
=947318989803-6bn6qk8qdgf4n4g3pfee6491hc0brc4i.apps.googleusercontent.com&redire
ct_uri=urn%3aietf%3awg%3aoauth%3a2.0%3aoob&response_type=code&scope=email%20http
s%3a%2f%2fwww.googleapis.com%2fauth%2fdocs.test%20https%3a%2f%2fwww.googleapis.c
om%2fauth%2fdrive%20https%3a%2f%2fwww.googleapis.com%2fauth%2fdrive.photos.reado
nly%20https%3a%2f%2fwww.googleapis.com%2fauth%2fpeopleapi.readonly

Enter your authorization code:
ůůůůůůůůůů
Mounted at /content/drive
```

[ ]:
```python
# using SQLite Table to read data.

con = sqlite3.connect('drive/My Drive/FFRDB/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 500000␣
↪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 Score != 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""", con)

# Give reviews with Score>3 a positive rating(1), and reviews with a score<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 (525814, 10)
```

```
[ ]:    Id  ...                                               Text
    0   1  ...  I have bought several of the Vitality canned d...
    1   2  ...  Product arrived labeled as Jumbo Salted Peanut...
    2   3  ...  This is a confection that has been around a fe...

    [3 rows x 10 columns]
```

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

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

```
(80668, 7)
```

```
[ ]:                UserId  ... COUNT(*)
    0  #oc-R115TNMSPFT9I7  ...        2
    1  #oc-R11D9D7SHXIJB9  ...        3
    2  #oc-R11DNU2NBKQ23Z  ...        2
    3  #oc-R11O5J5ZVQE25C  ...        3
    4  #oc-R12KPBODL2B5ZD  ...        2

    [5 rows x 7 columns]
```

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

```
[ ]: 393063
```

3 [2] Exploratory Data Analysis

3.1 [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:

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

```
[ ]:       Id  ...                                               Text
    0  78445  ...  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
```

```
1  138317  ...  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
2  138277  ...  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
3   73791  ...  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
4  155049  ...  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...

[5 rows x 10 columns]
```

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.

[ ]:
```
#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')
```

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

[ ]:
```
(364173, 10)
```

[ ]:
```
final.sort_values('Time',inplace=True)
print(final.head(5))
```

```
            Id  ...                                               Text
138706  150524  ...  this witty little book makes my son laugh at l...
138683  150501  ...  I can remember seeing the show when it aired o...
417839  451856  ...  Beetlejuice is a well written movie ... ever...
346055  374359  ...  A twist of rumplestiskin captured on film, sta...
417838  451855  ...  Beetlejuice is an excellent and funny movie. K...

[5 rows x 10 columns]
```

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

[ ]:
```
69.25890143662969
```

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

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

display.head()
```

[ ]:
```
      Id  ...                                              Text
0  64422  ...  My son loves spaghetti so I didn't hesitate or...
1  44737  ...  It was almost a 'love at first bite' - the per...

[2 rows x 10 columns]
```

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

[ ]:
```
#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()
```

```
(364171, 10)
```

[ ]:
```
1    307061
0     57110
Name: Score, dtype: int64
```

4 [3] Preprocessing

4.1 [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

[ ]:
```
# 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)
```

```
this witty little book makes my son laugh at loud. i recite it in the car as
we're driving along and he always can sing the refrain. he's learned about
whales, India, drooping roses:  i love all the new words this book  introduces
and the silliness of it all.  this is a classic book i am  willing to bet my son
will STILL be able to recite from memory when he is  in college
==================================================
I finally ordered a couple products from this seller for myself(not as gifts)
and I am really happy. This Jade Bonsai is really cool and it arrived fast and
in perfect condition. It's in my living room and I get tons of compliments. It's
already grown some too and the pot it came in is really nice, looks expensive!
Much bigger than I thought it would be even.  Thanks again!!
==================================================
I bought some of this tea when I was in Seattle and I have been dying to get
more.  It really is the best tea I have ever had.  It is great hot or cold.
==================================================
I would prefer freshly made brown rice, but that takes a long time to make and
isn't easy. This makes it convenient, and takes all the guess work out of making
it. I generally have been buying frozen organic brown rice, but that takes up
lots of freezer space. The fact that this is easy to store at room temperature
is a big plus. I'll be buying more.
==================================================
```

[ ]:
```
# remove urls from text python: https://stackoverflow.com/a/40823105/4084039
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)
```

```
this witty little book makes my son laugh at loud. i recite it in the car as
we're driving along and he always can sing the refrain. he's learned about
whales, India, drooping roses:  i love all the new words this book  introduces
and the silliness of it all.  this is a classic book i am  willing to bet my son
will STILL be able to recite from memory when he is  in college
```

[ ]:

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

```
this witty little book makes my son laugh at loud. i recite it in the car as
we're driving along and he always can sing the refrain. he's learned about
whales, India, drooping roses:  i love all the new words this book  introduces
and the silliness of it all.  this is a classic book i am  willing to bet my son
will STILL be able to recite from memory when he is  in college
==================================================
I finally ordered a couple products from this seller for myself(not as gifts)
and I am really happy. This Jade Bonsai is really cool and it arrived fast and
in perfect condition. It's in my living room and I get tons of compliments. It's
already grown some too and the pot it came in is really nice, looks expensive!
Much bigger than I thought it would be even.  Thanks again!!
==================================================
I bought some of this tea when I was in Seattle and I have been dying to get
more.  It really is the best tea I have ever had.  It is great hot or cold.
==================================================
```

```
I would prefer freshly made brown rice, but that takes a long time to make and
isn't easy. This makes it convenient, and takes all the guess work out of making
it. I generally have been buying frozen organic brown rice, but that takes up
lots of freezer space. The fact that this is easy to store at room temperature
is a big plus. I'll be buying more.
```

[ ]:
```
# 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
```

[ ]:
```
sent_1500 = decontracted(sent_1500)
print(sent_1500)
print("="*50)
```

```
I bought some of this tea when I was in Seattle and I have been dying to get
more.  It really is the best tea I have ever had.  It is great hot or cold.
==================================================
```

[ ]:
```
#remove words with numbers python: https://stackoverflow.com/a/18082370/4084039
sent_0 = re.sub("\S*\d\S*", "", sent_0).strip()
print(sent_0)
```

```
this witty little book makes my son laugh at loud. i recite it in the car as
we're driving along and he always can sing the refrain. he's learned about
whales, India, drooping roses:  i love all the new words this book  introduces
and the silliness of it all.  this is a classic book i am  willing to bet my son
will STILL be able to recite from memory when he is  in college
```

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

```
I bought some of this tea when I was in Seattle and I have been dying to get
more It really is the best tea I have ever had It is great hot or cold
```

[ ]:
```
final=final.sample(40000,random_state=23)
```

[ ]:
```
# Combining all the above stundents
from tqdm.notebook 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())
    preprocessed_reviews.append(sentance.strip())
```

```
HBox(children=(FloatProgress(value=0.0, max=40000.0), HTML(value='')))
```

[ ]:
```
preprocessed_reviews[1500]
```

[ ]:
```
'i think i am a granola expert i have tried many and let me tell you this is the
best with certified organic ingredients ambrosial granola grecian grove
antioxidant blend delivers nutrition and great taste i like the fact that every
spoonfull is loaded with organic fruits there is no added fat and is lightely
sweetened with healthy sweeteners like honey molasses and rice syrup all good
for you sweeteners ambrosial product'
```

5 Vectorizing sentences for LSTM input

[ ]:
```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test =␣
↪train_test_split(preprocessed_reviews,final['Score'].values,test_size=0.
↪3,random_state=0)
```

[ ]:
```
def concat(list):
    from tqdm.notebook import tqdm
    op= ' '
    print("making a Bag of words")
    for ele in tqdm(list):
        op = op + ' '+ str(ele)
```

```
    return op.split(' ')
```

[ ]:
```
# def fit(lst,top_word):
#   from tqdm.notebook import tqdm
#   corpus=[]
#   corpus=concat(lst)
#   print('generating word frequncy dictionry')
#   freq = [corpus.count(p) for p in tqdm(corpus)]
#   dic=dict(list(zip(corpus,freq)))
#   arr = [list(dic.items()) for d in dic]
#   print('returning word frequncy dataframe')
#   return pd.DataFrame(arr[0], columns=['word', 'freq']).
↪sort_values(by=['freq'], ascending=False,ignore_index=True).head(top_word)
```

[ ]:
```
# def fit(lst,top_word):
#   from tqdm.notebook import tqdm
#   import itertools
#   corpus=[]
#   dic={}
#   corpus=concat(lst)
#   print('generating word frequncy dictionry')

#   for p in tqdm(corpus):
#     freq=0
#     if p in dic.keys():
#       pass
#     else:
#       freq=(corpus.count(p))
#       dic[p]=freq
#   sort_orders = dict(sorted(dic.items(), key=lambda x: x[1], reverse=True))
#   out = dict(itertools.islice(sort_orders.items(), top_word))
#   print('returning word frequncy dataframe')
#   return pd.DataFrame([out])
```

[ ]:
```
def fit(lst,top_word):
  from tqdm.notebook import tqdm
  import itertools
  corpus=[]
  dic={}
  corpus=concat(lst)
  print('generating word frequency dictionry')

  for p in tqdm(corpus):
    freq=0
    if p in dic.keys():
      pass
    else:
      freq=(corpus.count(p))
```

```
    dic[p]=freq
  sort_orders = dict(sorted(dic.items(), key=lambda x: x[1], reverse=True))
  print('dictionary sorted')

  out = dict(itertools.islice(sort_orders.items(), top_word))
  print('top {} words extracted'.format(top_word))

  arr = list(out.keys())
  print('returnig dataframe')
  return np.array(arr)
```

[ ]:
```
def transform(lst,fit):
  doc=[]
  from tqdm.notebook import tqdm
  fit=fit.tolist()
  print('generating document list containing sentance list in vetor form')
  for sent in tqdm(lst):
    sent_vect=[]
    for word in sent.split(' '):
      try:
            idx = fit.index(str(word))+1
      except:
            idx = 0
      sent_vect.append(idx)
    doc.append(sent_vect)
  return doc
```

[ ]:
```
print(type(X_train[9]))
print(len(X_train[9].split(' ')))
print(X_train[9])
```

```
<class 'str'>
33
bought these regularly from the vending machine at college until of course they
stopped stocking them why i do not know i was happy to find them at amazon and
bought a case
```

[ ]:
```
print(type(X_train[1]))
print(len(X_train[1].split(' ')))
print(X_train[0])
```

```
<class 'str'>
47
my husband is a huge root beer fan so i got him this for christmas the root beer
was good but with shipping it comes to a lot of money after i ordered i found
out you can actually get all of these brands at cost plus for much cheaper since
you do not have to pay for shipping
```

[ ]:
```
print(type(X_train[24]))
print(len(X_train[24].split(' ')))
print(X_train[24])
```

```
<class 'str'>
22
light n fluffy less hulls than most interesting light bluish tint to the poppped
corn love the convenience of the microwave bags
```

[ ]:
```
ts_lst=[X_train[1],X_train[9],X_train[24]]
```

[ ]:
```
ts=concat(ts_lst)
print(len(ts))
print(ts)
```

```
making a Bag of words

HBox(children=(FloatProgress(value=0.0, max=3.0), HTML(value='')))


104
['', '', 'enjoyed', 'making', 'those', 'cookies', 'with', 'my', 'two', 'girls',
'and', 'yo', 'they', 'enjoyed', 'cracking', 'egg', 'and', 'mixing', 'it',
'then', 'watching', 'it', 'to', 'shape', 'up', 'and', 'get', 'ready', 'easy',
'to', 'make', 'fast', 'to', 'prepare', 'and', 'really', 'tasty', 'also',
'makes', 'a', 'good', 'project', 'for', 'kids', 'when', 'they', 'have',
'friends', 'over', 'bought', 'these', 'regularly', 'from', 'the', 'vending',
'machine', 'at', 'college', 'until', 'of', 'course', 'they', 'stopped',
'stocking', 'them', 'why', 'i', 'do', 'not', 'know', 'i', 'was', 'happy', 'to',
'find', 'them', 'at', 'amazon', 'and', 'bought', 'a', 'case', 'light', 'n',
'fluffy', 'less', 'hulls', 'than', 'most', 'interesting', 'light', 'bluish',
'tint', 'to', 'the', 'poppped', 'corn', 'love', 'the', 'convenience', 'of',
'the', 'microwave', 'bags']
```

[ ]:
```
X=fit(ts_lst,50)
```

```
making a Bag of words

HBox(children=(FloatProgress(value=0.0, max=3.0), HTML(value='')))


generating word frequency dictionry

HBox(children=(FloatProgress(value=0.0, max=104.0), HTML(value='')))
```

```
dictionary sorted
top 50 words extracted
returnig dataframe
```

[ ]:
```
X
```

[ ]:
```
array(['and', 'to', 'the', 'they', '', 'enjoyed', 'it', 'a', 'bought',
       'at', 'of', 'them', 'i', 'light', 'making', 'those', 'cookies',
       'with', 'my', 'two', 'girls', 'yo', 'cracking', 'egg', 'mixing',
       'then', 'watching', 'shape', 'up', 'get', 'ready', 'easy', 'make',
       'fast', 'prepare', 'really', 'tasty', 'also', 'makes', 'good',
       'project', 'for', 'kids', 'when', 'have', 'friends', 'over',
       'these', 'regularly', 'from'], dtype='<U9')
```

[ ]:
```
y=transform(ts_lst,X)
```

```
generating document list containing sentance list in vetor form

HBox(children=(FloatProgress(value=0.0, max=3.0), HTML(value='')))
```

[ ]:
```
for i in y:
  print(i)
```

```
[6, 15, 16, 17, 18, 19, 20, 21, 1, 22, 4, 6, 23, 24, 1, 25, 7, 26, 27, 7, 2, 28,
29, 1, 30, 31, 32, 2, 33, 34, 2, 35, 1, 36, 37, 38, 39, 8, 40, 41, 42, 43, 44,
4, 45, 46, 47]
[9, 48, 49, 50, 3, 0, 0, 10, 0, 0, 11, 0, 4, 0, 0, 12, 0, 13, 0, 0, 0, 13, 0, 0,
2, 0, 12, 10, 0, 1, 9, 8, 0]
[14, 0, 0, 0, 0, 0, 0, 0, 14, 0, 0, 2, 3, 0, 0, 0, 3, 0, 11, 3, 0, 0]
```

[ ]:
```
for i in ts_lst:
  print(i)
```

```
enjoyed making those cookies with my two girls and yo they enjoyed cracking egg
and mixing it then watching it to shape up and get ready easy to make fast to
prepare and really tasty also makes a good project for kids when they have
friends over
bought these regularly from the vending machine at college until of course they
stopped stocking them why i do not know i was happy to find them at amazon and
bought a case
light n fluffy less hulls than most interesting light bluish tint to the poppped
corn love the convenience of the microwave bags
```

```
[ ]: new_lst=X_train[1000:1005]
```

```
[ ]: y=transform(new_lst,X)
```

```
generating document list containing sentance list in vetor form

HBox(children=(FloatProgress(value=0.0, max=5.0), HTML(value='')))
```

```
[ ]: for i in y:
       print(i)
```

```
[13, 0, 0, 0, 8, 0, 0, 13, 0, 0, 0, 7, 0, 0, 13, 0, 0, 0, 19, 46, 0, 0, 0, 0, 4,
0, 7, 7, 0, 0, 3, 0, 7, 0, 7, 0]
[13, 0, 3, 0, 0, 0, 0, 1, 13, 0, 13, 0, 0, 0, 8, 0, 0, 0, 30, 0, 3, 0, 42, 3, 0,
0, 0, 0, 0, 0, 7, 0, 0, 0, 0, 3, 0, 13, 0, 2, 0, 0, 0, 0, 2, 0, 0, 19, 0, 0, 0,
39, 7, 0, 0, 0, 3, 0, 0, 3, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 42, 3, 0, 0, 0,
0, 7, 0, 0, 0, 0, 0]
[0, 0, 0, 44, 7, 0, 0, 0, 0, 0, 0, 42, 7, 0, 3, 0, 0, 0, 3, 0, 0, 7, 0, 0, 42,
0, 0, 0, 40, 0, 7, 0, 42, 0, 0, 18, 8, 0, 0, 0, 0, 0, 0, 7, 0, 8, 0, 11, 0, 0,
0, 0, 0, 7, 3, 0, 20, 0, 0, 0, 1, 3, 0, 0, 0, 0, 7, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0, 3, 0, 0, 0, 0, 0, 0, 11, 0, 0, 3, 0, 0, 0, 0, 0, 0, 7, 0, 0, 0, 0, 0, 0,
0, 11, 0, 0, 0, 18, 0, 2, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 7, 0, 0, 0, 0, 0,
7, 0, 0, 40, 42, 0, 7, 0, 0, 3, 0, 0, 0, 15, 0, 0, 0, 13, 0, 13, 0, 0, 42, 0, 0,
1, 0, 0, 0, 3, 0, 11, 3, 0, 13, 0, 0, 0, 1, 0, 0, 0, 2, 0, 0, 19, 0, 0, 13, 0,
0, 8, 0, 42, 0, 0, 44, 0, 0, 29, 13, 0, 0, 0, 2, 0, 3, 0, 0, 13, 0, 10, 3, 0, 1,
0, 0, 1, 0, 0, 8, 40, 0, 13, 45, 0, 0, 0, 1, 0, 45, 8, 0, 0, 3, 0, 0, 3, 0, 13,
0, 0, 0, 0, 7, 0, 0, 11, 3, 0, 0, 0, 0, 0, 33, 8, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
11, 0, 0, 0, 0, 13, 0, 0, 3, 0, 0, 0, 0, 50, 0, 0, 0, 0, 0, 0]
[13, 0, 8, 0, 0, 0, 0, 0, 0, 0, 0, 8, 0, 0, 0, 0, 0, 0, 3, 0, 0, 0, 0, 0, 0, 0,
13, 0, 2, 0, 3, 0, 0, 0, 44, 19, 0, 11, 0, 0, 0, 0, 0, 0, 3, 0, 13, 0, 0, 2, 0,
0, 0, 19, 0, 0, 0, 0, 0, 0, 0, 13, 0, 8, 0, 0, 0, 3, 0, 0, 0, 0, 11, 0, 20, 0,
13, 0, 0, 0, 19, 0, 0, 0, 29, 0, 0, 0, 3, 20, 0, 0, 0, 0, 0, 1, 13, 0, 0, 0, 2,
0, 8, 0, 0, 0, 0, 7, 0, 0, 0, 0, 7, 0, 0, 0, 0, 0, 0, 11, 0, 13, 0, 0, 0, 0, 0,
3, 0, 0, 0, 7, 0, 0, 8, 0, 0, 0, 2, 0, 0, 0, 0, 0, 7, 0, 0, 0, 3, 0, 0]
[48, 0, 0, 0, 0, 0, 0, 48, 0, 0, 42, 8, 0, 0, 0, 3, 0, 0, 4, 0, 0, 0, 0, 44, 13,
0, 2, 3, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]
```

```
[ ]: for i in new_lst:
       print(i)
```

```
i sent this as a gift so i cannot comment on it too much i do know that my
friends were very pleased once they received it it arrived on the date it said
it would
i use the goita chitosuma yuzu juice and i thought i would give this a try
```

```
because you get double the amount for the dollar well no you do not it is
diluted weaker than the goita i had to use times as much to put in my ice water
that makes it more expensive in the long run the goita is higher concentrate and
one can use or less as much for the same effect either way it is all better than
lemon
problem is ridiculous when it is in most grocery stores look for it in the spice
aisle on the bottom shelf it is salt for cryin out loud good thing it qualifies
for free shipping with a purchase problem description is wrong yes it is a pack
of three pounds but that is it the next two items contradict themselves and the
first one is wrong it does not contain iodine kosher salt by definition cannot
contain iodine the anti caking agent is yellow prussiate of soda so the third
statement is obviously wrong because it does contain an additive jeez pack
contains of poundstable salt mixed with iodine to prevent goiter and anti caking
agentcontains no additives problem contains an additive it is not pure salt so
it is no good for pickling it can turn the pickles mushy or making preserved
lemons which i love i was looking for kosher salt and could not remember the
name of the one i like so well and which is hard to find in my area so i just
did a search for kosher salt when this popped up i was quite surprise to see the
price so i looked at the product and was amazed and not in a good way i have
used this product and still have a box on the shelf in the pantry i will not be
buying it again because of the additives apparently morton does not make a salt
without additives even their sea salt has yellow prussiate of soda so sorry
morton i will buy the diamond crystal kosher salt from now on no additives just
salt
i had a terrible plugged drain that nothing would clear finally a friend
recommended that vinegar might dissolve the blockage this had so frustrated me
that i decided to buy the best vinegar available when my box of modena
extravecchio gold seal arrived in the mail i immediately went to work within
minutes my kitchen sink was flowing freely once again i am a bit upset about the
short listed shelf life of only two years i am afraid that my drain will stop up
again just after the two year shelf life has expired and i will be forced to
purchase a new case given that it is already years old it seems like an
unreasonable limitation but of course i would not risk going against the
manufacturer is recommendation it certainly commands a small premium compared to
other drain cleaner products but it is well worth the extra money
these taste great while here on amazon these are listed for a lower price than
the strawberry ones they still are higher than when i go to the local store if
you buy in bulk you should be saving money
```

[ ]:
```
fit_vect=fit(X_train,5000)
```

[ ]:
```
# dbfile1 = open('/content/drive/My Drive/FFRDB/lstm.pkl', 'wb')
# pickle.dump(fit_vect, dbfile1)
# dbfile1.close()
dbfile1 = open('/content/drive/My Drive/FFRDB/lstm.pkl', 'rb')
fit_vect = pickle.load(dbfile1)
```

[ ]:
```
fit_vect.shape
```

[ ]: (5000,)

```
[ ]: X_train=transform(X_train,fit_vect)
```

```
generating document list containing sentance list in vetor form

HBox(children=(FloatProgress(value=0.0, max=28000.0), HTML(value='')))
```

```
[ ]: # dbfile1 = open('/content/drive/My Drive/FFRDB/lstm2.pkl', 'wb')
     # pickle.dump([X_train,y_train], dbfile1)
     # dbfile1.close()
     dbfile1 = open('/content/drive/My Drive/FFRDB/lstm2.pkl', 'rb')
     X_train,y_train = pickle.load(dbfile1)
```

```
[ ]: print(len(X_train))
     print(len(y_train))
```

```
28000
28000
```

```
[ ]: X_test=transform(X_test,fit_vect)
```

```
generating document list containing sentance list in vetor form

HBox(children=(FloatProgress(value=0.0, max=12000.0), HTML(value='')))
```

```
[ ]: # dbfile1 = open('/content/drive/My Drive/FFRDB/lstm3.pkl', 'wb')
     # pickle.dump([X_test,y_test], dbfile1)
     # dbfile1.close()
     dbfile1 = open('/content/drive/My Drive/FFRDB/lstm3.pkl', 'rb')
     X_test,y_test = pickle.load(dbfile1)
```

```
[ ]: # Credits: https://machinelearningmastery.com/
      ↪sequence-classification-lstm-recurrent-neural-networks-python-keras/
     # LSTM for sequence classification in the IMDB dataset
     import numpy
     # from keras.datasets import imdb
     from keras.models import Sequential
     from keras.layers import Dense,Dropout
     from keras.layers import LSTM
     from keras.layers.embeddings import Embedding
     from keras.preprocessing import sequence
```

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

```
Using TensorFlow backend.
```

[ ]:
```
X_tr,y_tr=X_train,y_train
```

[ ]:
```
X_ts=X_test
y_ts=y_test
```

[ ]:
```
print(X_tr[1])
print(type(X_tr[1]))
print(len(X_tr[1]))
print(len(X_tr))
```

```
[499, 310, 219, 233, 17, 13, 119, 2671, 3, 0, 21, 499, 0, 1000, 3, 1094, 5, 110,
1576, 5, 7, 1036, 63, 3, 59, 823, 168, 7, 80, 399, 7, 1002, 3, 65, 218, 75, 152,
4, 28, 0, 12, 332, 49, 21, 15, 486, 121]
<class 'list'>
47
28000
```

[ ]:
```
max_review_length = 200
X_tr = sequence.pad_sequences(X_tr, maxlen=max_review_length)
X_ts = sequence.pad_sequences(X_ts, maxlen=max_review_length)
```

[ ]:
```
# truncate and/or pad input sequences
print(X_tr.shape)
print(X_tr[0])
```

```
(28000, 200)
[    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     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    13   346     6     4   540  1438  1368   460    24     2   153   304     9
    12   641     1  1438  1368    20    28    19    17   217     5   325     7     4
   171     8   323    93     2   188     2   107    56    16    32   245    59    41
     8    26   295    31   417   420    12    71   385   133    16    40    10    15
     7   559    12   217]
```

[ ]:
```
# create the model
top_words=5000
embedding_vecor_length = 32
model = Sequential()
model.add(Embedding(top_words+1, embedding_vecor_length,␣
 ↪input_length=max_review_length))
model.add(LSTM(100))
model.add(Dense(1, activation='sigmoid'))
model.compile(loss='binary_crossentropy', optimizer='adam',␣
 ↪metrics=['accuracy'])
print(model.summary())
#Refer: https://datascience.stackexchange.com/questions/10615/
 ↪number-of-parameters-in-an-lstm-model
```

```
Model: "sequential_14"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_14 (Embedding)     (None, 200, 32)           160032
_________________________________________________________________
lstm_14 (LSTM)               (None, 100)               53200
_________________________________________________________________
dense_14 (Dense)             (None, 1)                 101
=================================================================
Total params: 213,333
Trainable params: 213,333
Non-trainable params: 0
_________________________________________________________________
None
```

[ ]:
```
history=model.fit(X_tr, y_tr, validation_split=0.2,  nb_epoch=10, batch_size=64)
```

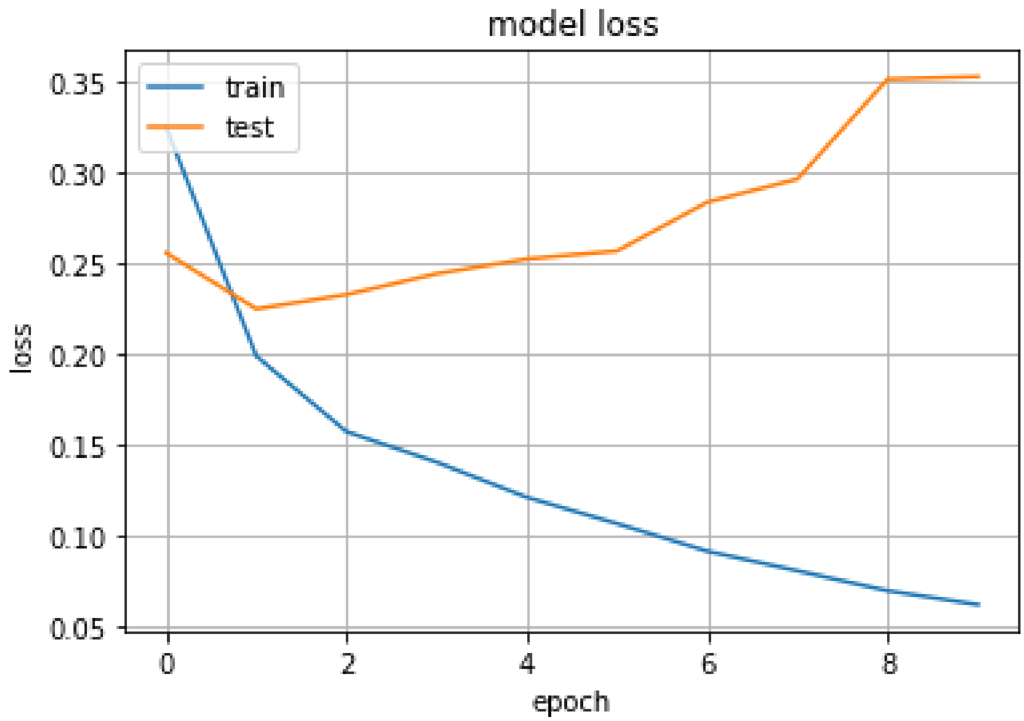
```
Train on 22400 samples, validate on 5600 samples
Epoch 1/10
22400/22400 [==============================] - 102s 5ms/step - loss: 0.3242 -
accuracy: 0.8716 - val_loss: 0.2552 - val_accuracy: 0.8943
Epoch 2/10
22400/22400 [==============================] - 108s 5ms/step - loss: 0.1983 -
accuracy: 0.9215 - val_loss: 0.2243 - val_accuracy: 0.9098
Epoch 3/10
22400/22400 [==============================] - 108s 5ms/step - loss: 0.1567 -
accuracy: 0.9419 - val_loss: 0.2322 - val_accuracy: 0.9134
Epoch 4/10
22400/22400 [==============================] - 106s 5ms/step - loss: 0.1399 -
accuracy: 0.9484 - val_loss: 0.2437 - val_accuracy: 0.9084
Epoch 5/10
22400/22400 [==============================] - 99s 4ms/step - loss: 0.1206 -
```

```
accuracy: 0.9561 - val_loss: 0.2518 - val_accuracy: 0.9016
Epoch 6/10
22400/22400 [==============================] - 99s 4ms/step - loss: 0.1061 -
accuracy: 0.9629 - val_loss: 0.2562 - val_accuracy: 0.9096
Epoch 7/10
22400/22400 [==============================] - 98s 4ms/step - loss: 0.0908 -
accuracy: 0.9675 - val_loss: 0.2831 - val_accuracy: 0.9071
Epoch 8/10
22400/22400 [==============================] - 98s 4ms/step - loss: 0.0800 -
accuracy: 0.9730 - val_loss: 0.2958 - val_accuracy: 0.9079
Epoch 9/10
22400/22400 [==============================] - 98s 4ms/step - loss: 0.0691 -
accuracy: 0.9773 - val_loss: 0.3508 - val_accuracy: 0.9046
Epoch 10/10
22400/22400 [==============================] - 98s 4ms/step - loss: 0.0615 -
accuracy: 0.9797 - val_loss: 0.3522 - val_accuracy: 0.8977
```

[ ]:
```
scores = model.evaluate(X_ts, y_ts, verbose=0)
print("Accuracy: %.2f%%" % (scores[1]*100))
```

```
Accuracy: 89.67%
```

[ ]:
```
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.grid()
plt.legend(['train', 'test'], loc='upper left')
plt.show()
```



[ ]:
```
# create the model
top_words=5000
embedding_vecor_length = 32
model2 = Sequential()
model2.add(Embedding(top_words+1, embedding_vecor_length,␣
↪input_length=max_review_length))
model2.add(LSTM(50))
model2.add(Dense(1, activation='sigmoid'))
model2.compile(loss='binary_crossentropy', optimizer='adam',␣
↪metrics=['accuracy'])
print(model2.summary())
#Refer: https://datascience.stackexchange.com/questions/10615/
↪number-of-parameters-in-an-lstm-model
```

```
Model: "sequential_15"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_15 (Embedding)     (None, 200, 32)           160032
_________________________________________________________________
lstm_15 (LSTM)               (None, 50)                16600
_________________________________________________________________
dense_15 (Dense)             (None, 1)                 51
=================================================================
```

```
Total params: 176,683
Trainable params: 176,683
Non-trainable params: 0
_________________________________________________________________
None
```

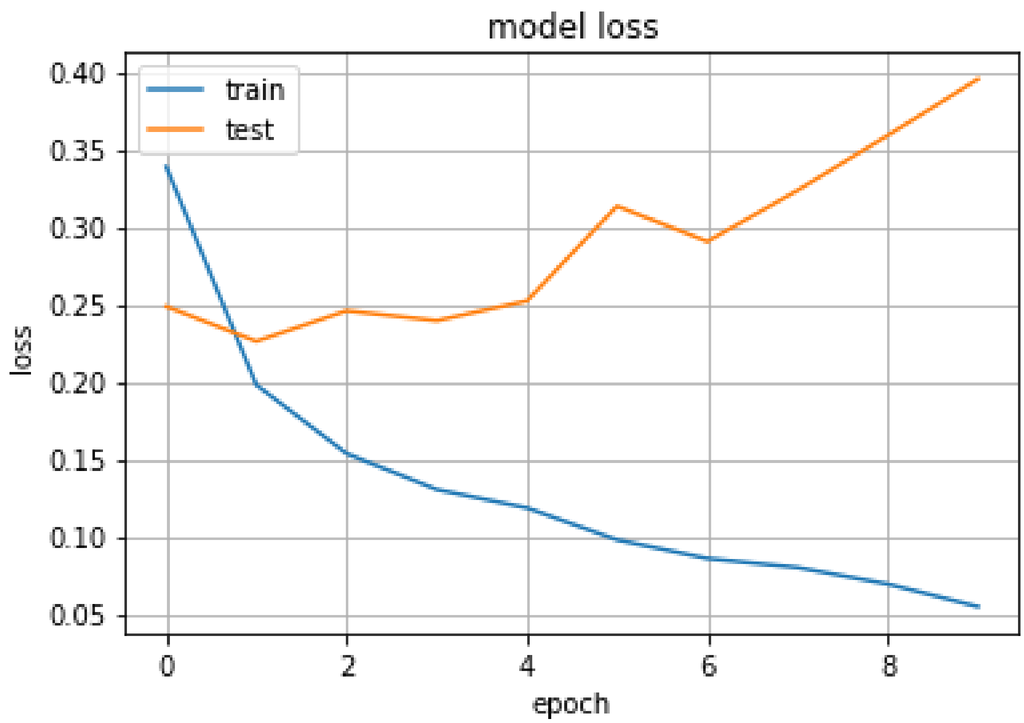
[ ]:
```
history2=model2.fit(X_tr, y_tr, validation_split=0.2,  nb_epoch=10,␣
 ↪batch_size=64)
```

```
Train on 22400 samples, validate on 5600 samples
Epoch 1/10
22400/22400 [==============================] - 56s 2ms/step - loss: 0.3388 -
accuracy: 0.8643 - val_loss: 0.2486 - val_accuracy: 0.8950
Epoch 2/10
22400/22400 [==============================] - 55s 2ms/step - loss: 0.1979 -
accuracy: 0.9206 - val_loss: 0.2261 - val_accuracy: 0.9084
Epoch 3/10
22400/22400 [==============================] - 54s 2ms/step - loss: 0.1536 -
accuracy: 0.9417 - val_loss: 0.2458 - val_accuracy: 0.8957
Epoch 4/10
22400/22400 [==============================] - 54s 2ms/step - loss: 0.1304 -
accuracy: 0.9513 - val_loss: 0.2394 - val_accuracy: 0.9096
Epoch 5/10
22400/22400 [==============================] - 54s 2ms/step - loss: 0.1185 -
accuracy: 0.9565 - val_loss: 0.2521 - val_accuracy: 0.9093
Epoch 6/10
22400/22400 [==============================] - 55s 2ms/step - loss: 0.0978 -
accuracy: 0.9655 - val_loss: 0.3133 - val_accuracy: 0.9102
Epoch 7/10
22400/22400 [==============================] - 55s 2ms/step - loss: 0.0858 -
accuracy: 0.9696 - val_loss: 0.2904 - val_accuracy: 0.9027
Epoch 8/10
22400/22400 [==============================] - 54s 2ms/step - loss: 0.0800 -
accuracy: 0.9725 - val_loss: 0.3235 - val_accuracy: 0.9045
Epoch 9/10
22400/22400 [==============================] - 54s 2ms/step - loss: 0.0693 -
accuracy: 0.9758 - val_loss: 0.3590 - val_accuracy: 0.9070
Epoch 10/10
22400/22400 [==============================] - 54s 2ms/step - loss: 0.0547 -
accuracy: 0.9824 - val_loss: 0.3954 - val_accuracy: 0.9000
```

[ ]:
```
scores = model2.evaluate(X_ts, y_ts, verbose=0)
print("Accuracy: %.2f%%" % (scores[1]*100))
```

```
Accuracy: 90.13%
```

[ ]:
```
plt.plot(history2.history['loss'])
plt.plot(history2.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.grid()
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()
```



[ ]:
```
# create the model
top_words=5000
embedding_vecor_length = 32
model3 = Sequential()
model3.add(Embedding(top_words+1, embedding_vecor_length,␣
 ↪input_length=max_review_length))
model3.add(Dropout(0.3))
model3.add(LSTM(150))
model3.add(Dropout(0.3))
model3.add(Dense(1, activation='sigmoid'))
model3.compile(loss='binary_crossentropy', optimizer='adam',␣
 ↪metrics=['accuracy'])
print(model3.summary())
#Refer: https://datascience.stackexchange.com/questions/10615/
 ↪number-of-parameters-in-an-lstm-model
```

```
Model: "sequential_18"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_18 (Embedding)     (None, 200, 32)           160032
_________________________________________________________________
dropout_1 (Dropout)          (None, 200, 32)           0
_________________________________________________________________
lstm_16 (LSTM)               (None, 150)               109800
_________________________________________________________________
dropout_2 (Dropout)          (None, 150)               0
_________________________________________________________________
dense_16 (Dense)             (None, 1)                 151
=================================================================
Total params: 269,983
Trainable params: 269,983
Non-trainable params: 0
_________________________________________________________________
None
```

[ ]:
```
history3=model3.fit(X_tr, y_tr, validation_split=0.2,  nb_epoch=10,␣
 ↪batch_size=64)
```

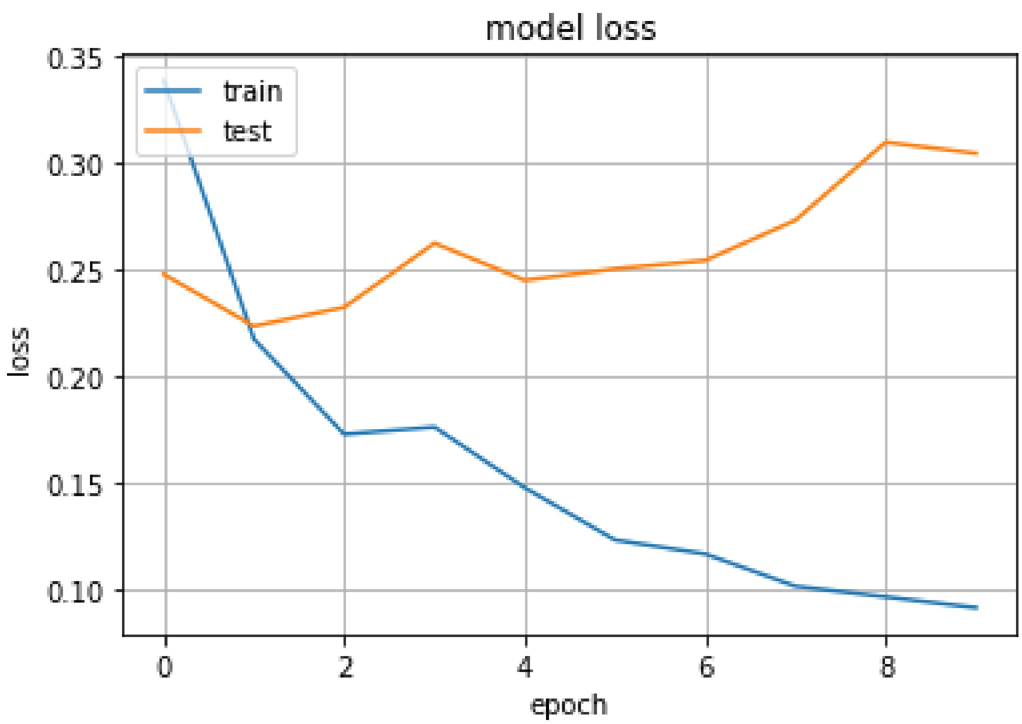
```
Train on 22400 samples, validate on 5600 samples
Epoch 1/10
22400/22400 [==============================] - 192s 9ms/step - loss: 0.3387 -
accuracy: 0.8688 - val_loss: 0.2480 - val_accuracy: 0.9009
Epoch 2/10
22400/22400 [==============================] - 195s 9ms/step - loss: 0.2176 -
accuracy: 0.9146 - val_loss: 0.2237 - val_accuracy: 0.9123
Epoch 3/10
22400/22400 [==============================] - 192s 9ms/step - loss: 0.1730 -
accuracy: 0.9346 - val_loss: 0.2325 - val_accuracy: 0.9161
Epoch 4/10
22400/22400 [==============================] - 186s 8ms/step - loss: 0.1764 -
accuracy: 0.9312 - val_loss: 0.2625 - val_accuracy: 0.9139
Epoch 5/10
22400/22400 [==============================] - 186s 8ms/step - loss: 0.1480 -
accuracy: 0.9425 - val_loss: 0.2452 - val_accuracy: 0.9125
Epoch 6/10
22400/22400 [==============================] - 192s 9ms/step - loss: 0.1235 -
accuracy: 0.9546 - val_loss: 0.2505 - val_accuracy: 0.9052
Epoch 7/10
22400/22400 [==============================] - 184s 8ms/step - loss: 0.1170 -
accuracy: 0.9579 - val_loss: 0.2544 - val_accuracy: 0.9023
Epoch 8/10
22400/22400 [==============================] - 191s 9ms/step - loss: 0.1018 -
```

```
accuracy: 0.9622 - val_loss: 0.2732 - val_accuracy: 0.8993
Epoch 9/10
22400/22400 [==============================] - 194s 9ms/step - loss: 0.0968 -
accuracy: 0.9656 - val_loss: 0.3098 - val_accuracy: 0.9084
Epoch 10/10
22400/22400 [==============================] - 186s 8ms/step - loss: 0.0918 -
accuracy: 0.9677 - val_loss: 0.3046 - val_accuracy: 0.9013
```

[ ]:
```
scores = model3.evaluate(X_ts, y_ts, verbose=0)
print("Accuracy: %.2f%%" % (scores[1]*100))
```

```
Accuracy: 90.38%
```

[ ]:
```
plt.plot(history3.history['loss'])
plt.plot(history3.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.grid()
plt.show()
```



[ ]:
```
! pip install --upgrade keras
```

```
Collecting keras
  Downloading https://files.pythonhosted.org/packages/44/e1/dc0757b20b56c980b555
3c1b5c4c32d378c7055ab7bfa92006801ad359ab/Keras-2.4.3-py2.py3-none-any.whl
Requirement already satisfied, skipping upgrade: h5py in
/usr/local/lib/python3.6/dist-packages (from keras) (2.10.0)
Requirement already satisfied, skipping upgrade: numpy>=1.9.1 in
/usr/local/lib/python3.6/dist-packages (from keras) (1.18.5)
Requirement already satisfied, skipping upgrade: pyyaml in
/usr/local/lib/python3.6/dist-packages (from keras) (3.13)
Requirement already satisfied, skipping upgrade: scipy>=0.14 in
/usr/local/lib/python3.6/dist-packages (from keras) (1.4.1)
Requirement already satisfied, skipping upgrade: six in /usr/local/lib/python3.6
/dist-packages (from h5py->keras) (1.12.0)
Installing collected packages: keras
  Found existing installation: Keras 2.3.1
    Uninstalling Keras-2.3.1:
      Successfully uninstalled Keras-2.3.1
Successfully installed keras-2.4.3
```

[ ]:
```
!pip uninstall tensorflow
```

```
Uninstalling tensorflow-1.13.2:
  Would remove:
    /usr/local/bin/freeze_graph
    /usr/local/bin/saved_model_cli
    /usr/local/bin/tensorboard
    /usr/local/bin/tf_upgrade_v2
    /usr/local/bin/tflite_convert
    /usr/local/bin/toco
    /usr/local/bin/toco_from_protos
    /usr/local/lib/python3.6/dist-packages/tensorflow-1.13.2.dist-info/*
    /usr/local/lib/python3.6/dist-packages/tensorflow/*
Proceed (y/n)? y
  Successfully uninstalled tensorflow-1.13.2
```

[ ]:
```
! pip install tensorflow==2.2.0
```

```
Collecting tensorflow==2.2.0
  Downloading https://files.pythonhosted.org/packages/3d/be/679ce5254a8c8d
07470efb4a4c00345fae91f766e64f1c2aece8796d7218/tensorflow-2.2.0-cp36-cp36m-
manylinux2010_x86_64.whl (516.2MB)
     || 516.2MB 32kB/s
Requirement already satisfied: scipy==1.4.1; python_version >= "3" in
/usr/local/lib/python3.6/dist-packages (from tensorflow==2.2.0) (1.4.1)
Requirement already satisfied: numpy<2.0,>=1.16.0 in /usr/local/lib/python3.6
/dist-packages (from tensorflow==2.2.0) (1.18.5)
Requirement already satisfied: wheel>=0.26; python_version >= "3" in
```

```
/usr/local/lib/python3.6/dist-packages (from tensorflow==2.2.0) (0.34.2)
Requirement already satisfied: gast==0.3.3 in /usr/local/lib/python3.6/dist-
packages (from tensorflow==2.2.0) (0.3.3)
Requirement already satisfied: google-pasta>=0.1.8 in /usr/local/lib/python3.6
/dist-packages (from tensorflow==2.2.0) (0.2.0)
Collecting tensorboard<2.3.0,>=2.2.0
  Downloading https://files.pythonhosted.org/packages/1d/74/0a6fcb206dcc72
a6da9a62dd81784bfdbff5fedb099982861dc2219014fb/tensorboard-2.2.2-py3-none-
any.whl (3.0MB)
     || 3.0MB 47.2MB/s
Requirement already satisfied: opt-einsum>=2.3.2 in
/usr/local/lib/python3.6/dist-packages (from tensorflow==2.2.0) (3.2.1)
Requirement already satisfied: astunparse==1.6.3 in /usr/local/lib/python3.6
/dist-packages (from tensorflow==2.2.0) (1.6.3)
Requirement already satisfied: keras-preprocessing>=1.1.0 in
/usr/local/lib/python3.6/dist-packages (from tensorflow==2.2.0) (1.1.2)
Requirement already satisfied: h5py<2.11.0,>=2.10.0 in /usr/local/lib/python3.6
/dist-packages (from tensorflow==2.2.0) (2.10.0)
Requirement already satisfied: six>=1.12.0 in /usr/local/lib/python3.6/dist-
packages (from tensorflow==2.2.0) (1.12.0)
Requirement already satisfied: wrapt>=1.11.1 in /usr/local/lib/python3.6/dist-
packages (from tensorflow==2.2.0) (1.12.1)
Requirement already satisfied: termcolor>=1.1.0 in /usr/local/lib/python3.6
/dist-packages (from tensorflow==2.2.0) (1.1.0)
Requirement already satisfied: grpcio>=1.8.6 in /usr/local/lib/python3.6/dist-
packages (from tensorflow==2.2.0) (1.30.0)
Requirement already satisfied: absl-py>=0.7.0 in /usr/local/lib/python3.6/dist-
packages (from tensorflow==2.2.0) (0.9.0)
Requirement already satisfied: protobuf>=3.8.0 in /usr/local/lib/python3.6/dist-
packages (from tensorflow==2.2.0) (3.12.2)
Collecting tensorflow-estimator<2.3.0,>=2.2.0
  Downloading https://files.pythonhosted.org/packages/a4/f5/926ae53d6a226e
c0fda5208e0e581cffed895ccc89e36ba76a8e60895b78/tensorflow_estimator-2.2.0-py2.py
3-none-any.whl (454kB)
     || 460kB 46.0MB/s
Requirement already satisfied: google-auth<2,>=1.6.3 in
/usr/local/lib/python3.6/dist-packages (from
tensorboard<2.3.0,>=2.2.0->tensorflow==2.2.0) (1.17.2)
Requirement already satisfied: google-auth-oauthlib<0.5,>=0.4.1 in
/usr/local/lib/python3.6/dist-packages (from
tensorboard<2.3.0,>=2.2.0->tensorflow==2.2.0) (0.4.1)
Requirement already satisfied: tensorboard-plugin-wit>=1.6.0 in
/usr/local/lib/python3.6/dist-packages (from
tensorboard<2.3.0,>=2.2.0->tensorflow==2.2.0) (1.7.0)
Requirement already satisfied: werkzeug>=0.11.15 in /usr/local/lib/python3.6
/dist-packages (from tensorboard<2.3.0,>=2.2.0->tensorflow==2.2.0) (1.0.1)
Requirement already satisfied: markdown>=2.6.8 in /usr/local/lib/python3.6/dist-
packages (from tensorboard<2.3.0,>=2.2.0->tensorflow==2.2.0) (3.2.2)
```

```
Requirement already satisfied: requests<3,>=2.21.0 in /usr/local/lib/python3.6
/dist-packages (from tensorboard<2.3.0,>=2.2.0->tensorflow==2.2.0) (2.23.0)
Requirement already satisfied: setuptools>=41.0.0 in /usr/local/lib/python3.6
/dist-packages (from tensorboard<2.3.0,>=2.2.0->tensorflow==2.2.0) (49.1.0)
Requirement already satisfied: rsa<5,>=3.1.4; python_version >= "3" in
/usr/local/lib/python3.6/dist-packages (from google-
auth<2,>=1.6.3->tensorboard<2.3.0,>=2.2.0->tensorflow==2.2.0) (4.6)
Requirement already satisfied: cachetools<5.0,>=2.0.0 in
/usr/local/lib/python3.6/dist-packages (from google-
auth<2,>=1.6.3->tensorboard<2.3.0,>=2.2.0->tensorflow==2.2.0) (4.1.1)
Requirement already satisfied: pyasn1-modules>=0.2.1 in /usr/local/lib/python3.6
/dist-packages (from google-
auth<2,>=1.6.3->tensorboard<2.3.0,>=2.2.0->tensorflow==2.2.0) (0.2.8)
Requirement already satisfied: requests-oauthlib>=0.7.0 in
/usr/local/lib/python3.6/dist-packages (from google-auth-
oauthlib<0.5,>=0.4.1->tensorboard<2.3.0,>=2.2.0->tensorflow==2.2.0) (1.3.0)
Requirement already satisfied: importlib-metadata; python_version < "3.8" in
/usr/local/lib/python3.6/dist-packages (from
markdown>=2.6.8->tensorboard<2.3.0,>=2.2.0->tensorflow==2.2.0) (1.7.0)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.6
/dist-packages (from
requests<3,>=2.21.0->tensorboard<2.3.0,>=2.2.0->tensorflow==2.2.0) (2020.6.20)
Requirement already satisfied: urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1 in
/usr/local/lib/python3.6/dist-packages (from
requests<3,>=2.21.0->tensorboard<2.3.0,>=2.2.0->tensorflow==2.2.0) (1.24.3)
Requirement already satisfied: chardet<4,>=3.0.2 in /usr/local/lib/python3.6
/dist-packages (from
requests<3,>=2.21.0->tensorboard<2.3.0,>=2.2.0->tensorflow==2.2.0) (3.0.4)
Requirement already satisfied: idna<3,>=2.5 in /usr/local/lib/python3.6/dist-
packages (from
requests<3,>=2.21.0->tensorboard<2.3.0,>=2.2.0->tensorflow==2.2.0) (2.10)
Requirement already satisfied: pyasn1>=0.1.3 in /usr/local/lib/python3.6/dist-
packages (from rsa<5,>=3.1.4; python_version >= "3"->google-
auth<2,>=1.6.3->tensorboard<2.3.0,>=2.2.0->tensorflow==2.2.0) (0.4.8)
Requirement already satisfied: oauthlib>=3.0.0 in /usr/local/lib/python3.6/dist-
packages (from requests-oauthlib>=0.7.0->google-auth-
oauthlib<0.5,>=0.4.1->tensorboard<2.3.0,>=2.2.0->tensorflow==2.2.0) (3.1.0)
Requirement already satisfied: zipp>=0.5 in /usr/local/lib/python3.6/dist-
packages (from importlib-metadata; python_version <
"3.8"->markdown>=2.6.8->tensorboard<2.3.0,>=2.2.0->tensorflow==2.2.0) (3.1.0)
Installing collected packages: tensorboard, tensorflow-estimator, tensorflow
  Found existing installation: tensorboard 1.13.1
    Uninstalling tensorboard-1.13.1:
      Successfully uninstalled tensorboard-1.13.1
  Found existing installation: tensorflow-estimator 1.13.0
    Uninstalling tensorflow-estimator-1.13.0:
      Successfully uninstalled tensorflow-estimator-1.13.0
Successfully installed tensorboard-2.2.2 tensorflow-2.2.0 tensorflow-
```

```
estimator-2.2.0
```

[ ]:
```python
# create the model
import tensorflow as tf
from tensorflow.keras.layers import Dense,Dropout,LSTM
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding



top_words=5000
embedding_vecor_length = 32

model4 = Sequential()
model4.add(Embedding(top_words+1, embedding_vecor_length,␣
 ↪input_length=max_review_length))
model4.add(Dropout(0.3))
model4.add(LSTM(128,return_sequences=True))
model4.add(Dropout(0.3))
model4.add(LSTM(32))
model4.add(Dropout(0.3))
model4.add(Dense(32,activation='relu'))
model4.add(Dense(1, activation='relu'))
model4.compile(loss='binary_crossentropy', optimizer='adam',␣
 ↪metrics=['accuracy'])
print(model4.summary())
#Refer: https://datascience.stackexchange.com/questions/10615/
 ↪number-of-parameters-in-an-lstm-model
```

```
Model: "sequential_3"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_2 (Embedding)      (None, 200, 32)           160032
_________________________________________________________________
dropout_4 (Dropout)          (None, 200, 32)           0
_________________________________________________________________
lstm_2 (LSTM)                (None, 200, 128)          82432
_________________________________________________________________
dropout_5 (Dropout)          (None, 200, 128)          0
_________________________________________________________________
lstm_3 (LSTM)                (None, 32)                20608
_________________________________________________________________
dropout_6 (Dropout)          (None, 32)                0
_________________________________________________________________
dense_2 (Dense)              (None, 32)                1056
_________________________________________________________________
```

```
dense_3 (Dense)              (None, 1)                 33
=================================================================
Total params: 264,161
Trainable params: 264,161
Non-trainable params: 0
_________________________________________________________________
None
```

[ ]:
```
history4=model4.fit(X_tr, y_tr, validation_split=0.2, epochs=100, batch_size=64)
```

```
Epoch 1/100
350/350 [==============================] - 9s 26ms/step - loss: 2.3543 -
accuracy: 0.8243 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 2/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 3/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 4/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 5/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 6/100
350/350 [==============================] - 9s 24ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 7/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 8/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 9/100
350/350 [==============================] - 9s 24ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 10/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 11/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 12/100
350/350 [==============================] - 9s 24ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 13/100
```

```
350/350 [==============================] - 9s 24ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 14/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 15/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 16/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 17/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 18/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 19/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 20/100
350/350 [==============================] - 9s 24ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 21/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 22/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 23/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 24/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 25/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 26/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 27/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 28/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 29/100
```

```
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 30/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 31/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 32/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 33/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 34/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 35/100
350/350 [==============================] - 9s 24ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 36/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 37/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 38/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 39/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 40/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 41/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 42/100
350/350 [==============================] - 9s 24ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 43/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 44/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 45/100
```

```
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 46/100
350/350 [==============================] - 9s 24ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 47/100
350/350 [==============================] - 9s 24ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 48/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 49/100
350/350 [==============================] - 9s 24ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 50/100
350/350 [==============================] - 8s 24ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 51/100
350/350 [==============================] - 9s 24ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 52/100
350/350 [==============================] - 9s 24ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 53/100
350/350 [==============================] - 9s 24ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 54/100
350/350 [==============================] - 9s 24ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 55/100
350/350 [==============================] - 9s 24ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 56/100
350/350 [==============================] - 9s 24ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 57/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 58/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 59/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 60/100
350/350 [==============================] - 8s 24ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 61/100
```

```
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 62/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 63/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 64/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 65/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 66/100
350/350 [==============================] - 9s 24ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 67/100
350/350 [==============================] - 9s 24ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 68/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 69/100
350/350 [==============================] - 8s 24ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 70/100
350/350 [==============================] - 9s 24ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 71/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 72/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 73/100
350/350 [==============================] - 9s 24ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 74/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 75/100
350/350 [==============================] - 9s 24ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 76/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 77/100
```

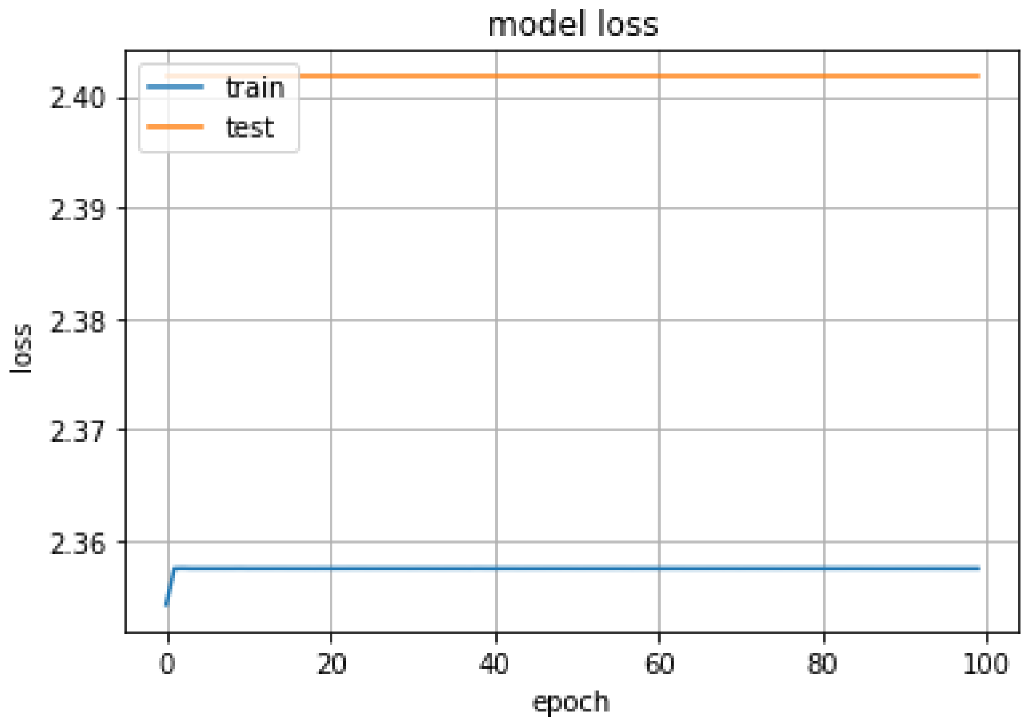
```
350/350 [==============================] - 9s 24ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 78/100
350/350 [==============================] - 9s 24ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 79/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 80/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 81/100
350/350 [==============================] - 8s 24ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 82/100
350/350 [==============================] - 9s 24ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 83/100
350/350 [==============================] - 8s 24ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 84/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 85/100
350/350 [==============================] - 8s 24ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 86/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 87/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 88/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 89/100
350/350 [==============================] - 8s 24ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 90/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 91/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 92/100
350/350 [==============================] - 9s 24ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 93/100
```

```
350/350 [==============================] - 8s 24ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 94/100
350/350 [==============================] - 9s 24ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 95/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 96/100
350/350 [==============================] - 9s 24ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 97/100
350/350 [==============================] - 8s 24ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 98/100
350/350 [==============================] - 9s 25ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 99/100
350/350 [==============================] - 9s 24ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
Epoch 100/100
350/350 [==============================] - 9s 24ms/step - loss: 2.3575 -
accuracy: 0.8454 - val_loss: 2.4018 - val_accuracy: 0.8425
```

[ ]:
```python
scores = model4.evaluate(X_ts, y_ts, verbose=0)
print("Accuracy: %.2f%%" % (scores[1]*100))
```

```
Accuracy: 84.72%
```

[ ]:
```python
plt.plot(history4.history['loss'])
plt.plot(history4.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.grid()
plt.show()
```



[78]:
```
# create the model
import tensorflow as tf
from tensorflow.keras.layers import Dense,Dropout,LSTM
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding

top_words=5000
embedding_vecor_length = 32

model5 = Sequential()
model5.add(Embedding(top_words+1, embedding_vecor_length,␣
 ↪input_length=max_review_length))
model5.add(Dropout(0.3))
model5.add(LSTM(128,return_sequences=True))
model5.add(Dropout(0.3))
model5.add(LSTM(64,return_sequences=True))
model5.add(Dropout(0.3))
model5.add(LSTM(32))
model5.add(Dropout(0.3))
model5.add(Dense(32,activation='relu'))
model5.add(Dense(1, activation='relu'))

model5.compile(loss='binary_crossentropy', optimizer='adam',␣
 ↪metrics=['accuracy'])
```

```python
print(model5.summary())
```

```
Model: "sequential_10"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_9 (Embedding)      (None, 200, 32)           160032
_________________________________________________________________
dropout_25 (Dropout)         (None, 200, 32)           0
_________________________________________________________________
lstm_16 (LSTM)               (None, 200, 128)          82432
_________________________________________________________________
dropout_26 (Dropout)         (None, 200, 128)          0
_________________________________________________________________
lstm_17 (LSTM)               (None, 200, 64)           49408
_________________________________________________________________
dropout_27 (Dropout)         (None, 200, 64)           0
_________________________________________________________________
lstm_18 (LSTM)               (None, 32)                12416
_________________________________________________________________
dropout_28 (Dropout)         (None, 32)                0
_________________________________________________________________
dense_16 (Dense)             (None, 32)                1056
_________________________________________________________________
dense_17 (Dense)             (None, 1)                 33
=================================================================
Total params: 305,377
Trainable params: 305,377
Non-trainable params: 0
_________________________________________________________________
None
```

[79]:
```python
history5=model5.fit(X_tr, y_tr, validation_split=0.2, epochs=30, batch_size=64)
```

```
Epoch 1/30
350/350 [==============================] - 13s 36ms/step - loss: 0.8090 -
accuracy: 0.7314 - val_loss: 0.4353 - val_accuracy: 0.8425
Epoch 2/30
350/350 [==============================] - 12s 33ms/step - loss: 0.5157 -
accuracy: 0.8279 - val_loss: 0.4879 - val_accuracy: 0.8486
Epoch 3/30
350/350 [==============================] - 12s 33ms/step - loss: 0.4472 -
accuracy: 0.8466 - val_loss: 0.5266 - val_accuracy: 0.8827
Epoch 4/30
350/350 [==============================] - 12s 33ms/step - loss: 0.3955 -
accuracy: 0.8697 - val_loss: 0.5453 - val_accuracy: 0.8879
Epoch 5/30
```

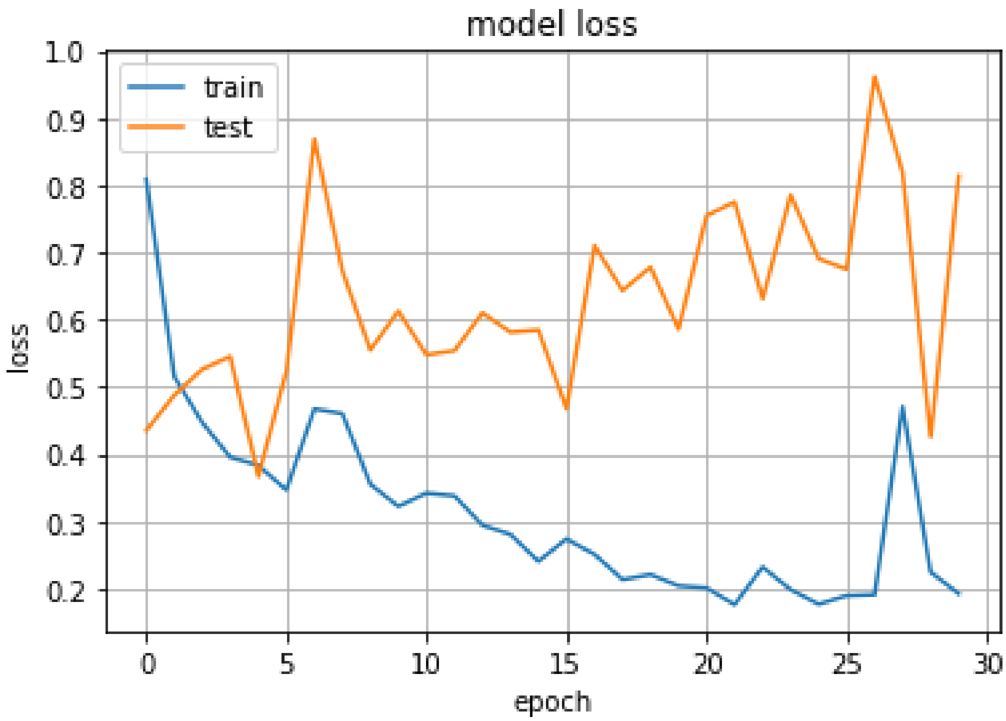
```
350/350 [==============================] - 11s 33ms/step - loss: 0.3836 -
accuracy: 0.8685 - val_loss: 0.3671 - val_accuracy: 0.8666
Epoch 6/30
350/350 [==============================] - 11s 33ms/step - loss: 0.3469 -
accuracy: 0.8987 - val_loss: 0.5236 - val_accuracy: 0.8936
Epoch 7/30
350/350 [==============================] - 12s 33ms/step - loss: 0.4674 -
accuracy: 0.7927 - val_loss: 0.8687 - val_accuracy: 0.6266
Epoch 8/30
350/350 [==============================] - 11s 33ms/step - loss: 0.4605 -
accuracy: 0.8346 - val_loss: 0.6731 - val_accuracy: 0.8768
Epoch 9/30
350/350 [==============================] - 11s 33ms/step - loss: 0.3556 -
accuracy: 0.9081 - val_loss: 0.5550 - val_accuracy: 0.8759
Epoch 10/30
350/350 [==============================] - 12s 33ms/step - loss: 0.3225 -
accuracy: 0.9070 - val_loss: 0.6131 - val_accuracy: 0.8927
Epoch 11/30
350/350 [==============================] - 11s 33ms/step - loss: 0.3423 -
accuracy: 0.8900 - val_loss: 0.5478 - val_accuracy: 0.8755
Epoch 12/30
350/350 [==============================] - 11s 33ms/step - loss: 0.3383 -
accuracy: 0.8988 - val_loss: 0.5540 - val_accuracy: 0.8871
Epoch 13/30
350/350 [==============================] - 11s 33ms/step - loss: 0.2944 -
accuracy: 0.9190 - val_loss: 0.6102 - val_accuracy: 0.8818
Epoch 14/30
350/350 [==============================] - 12s 33ms/step - loss: 0.2809 -
accuracy: 0.9244 - val_loss: 0.5815 - val_accuracy: 0.8948
Epoch 15/30
350/350 [==============================] - 11s 32ms/step - loss: 0.2407 -
accuracy: 0.9419 - val_loss: 0.5848 - val_accuracy: 0.9009
Epoch 16/30
350/350 [==============================] - 12s 33ms/step - loss: 0.2741 -
accuracy: 0.9198 - val_loss: 0.4679 - val_accuracy: 0.8716
Epoch 17/30
350/350 [==============================] - 11s 33ms/step - loss: 0.2510 -
accuracy: 0.9360 - val_loss: 0.7102 - val_accuracy: 0.8909
Epoch 18/30
350/350 [==============================] - 12s 33ms/step - loss: 0.2137 -
accuracy: 0.9440 - val_loss: 0.6437 - val_accuracy: 0.8950
Epoch 19/30
350/350 [==============================] - 11s 33ms/step - loss: 0.2211 -
accuracy: 0.9516 - val_loss: 0.6784 - val_accuracy: 0.9007
Epoch 20/30
350/350 [==============================] - 11s 33ms/step - loss: 0.2045 -
accuracy: 0.9516 - val_loss: 0.5861 - val_accuracy: 0.8682
Epoch 21/30
```

```
350/350 [==============================] - 11s 33ms/step - loss: 0.2014 -
accuracy: 0.9571 - val_loss: 0.7548 - val_accuracy: 0.8929
Epoch 22/30
350/350 [==============================] - 11s 33ms/step - loss: 0.1765 -
accuracy: 0.9652 - val_loss: 0.7751 - val_accuracy: 0.8989
Epoch 23/30
350/350 [==============================] - 12s 33ms/step - loss: 0.2322 -
accuracy: 0.9452 - val_loss: 0.6316 - val_accuracy: 0.8804
Epoch 24/30
350/350 [==============================] - 11s 33ms/step - loss: 0.1988 -
accuracy: 0.9504 - val_loss: 0.7856 - val_accuracy: 0.8930
Epoch 25/30
350/350 [==============================] - 11s 33ms/step - loss: 0.1771 -
accuracy: 0.9672 - val_loss: 0.6909 - val_accuracy: 0.8879
Epoch 26/30
350/350 [==============================] - 12s 33ms/step - loss: 0.1899 -
accuracy: 0.9616 - val_loss: 0.6753 - val_accuracy: 0.8893
Epoch 27/30
350/350 [==============================] - 12s 33ms/step - loss: 0.1913 -
accuracy: 0.9540 - val_loss: 0.9616 - val_accuracy: 0.8995
Epoch 28/30
350/350 [==============================] - 12s 33ms/step - loss: 0.4709 -
accuracy: 0.7877 - val_loss: 0.8192 - val_accuracy: 0.8798
Epoch 29/30
350/350 [==============================] - 12s 34ms/step - loss: 0.2248 -
accuracy: 0.9415 - val_loss: 0.4259 - val_accuracy: 0.8670
Epoch 30/30
350/350 [==============================] - 12s 34ms/step - loss: 0.1927 -
accuracy: 0.9598 - val_loss: 0.8141 - val_accuracy: 0.8948
```

[80]:
```
scores = model5.evaluate(X_ts, y_ts, verbose=0)
print("Accuracy: %.2f%%" % (scores[1]*100))
```

```
Accuracy: 89.72%
```

[81]:
```
plt.plot(history5.history['loss'])
plt.plot(history5.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.grid()
plt.show()
```



[86]:
```
from prettytable import PrettyTable
x = PrettyTable()
x.field_names = ["S.NO.", "architecture", "Epochs", "Test Accuracy"]
x.add_row(["1", "Keras LSTM(100)", "10","89.67%"])
x.add_row(["2", "Keras LSTM(50)","10","90.13%"])
x.add_row(["3", "Keras LSTM(50) + Dropouts", "10","90.38%"])
x.add_row(["4", "TenserFlow LSTM(128,32)+ Dense(32,1)+Dropouts","100","84.72%"])
x.add_row(["5", "TenserFlow LSTM(128,64,32)+ Dense(32,1)+Dropouts","30","89.
 ↪72%"])
print(x)
```

```
+--------+-------------------------------------------------+--------+-----------
----+
| S.NO. |                   architecture                  | Epochs | Test
Accuracy |
+--------+-------------------------------------------------+--------+-----------
----+
|   1    |                 Keras LSTM(100)                 |   10   |    89.67%
|
|   2    |                  Keras LSTM(50)                 |   10   |    90.13%
|
|   3    |            Keras LSTM(50) + Dropouts            |   10   |    90.38%
|
|   4    |  TenserFlow LSTM(128,32)+ Dense(32,1)+Dropouts  |  100   |    84.72%
```

```
|
|   5   | TenserFlow LSTM(128,64,32)+ Dense(32,1)+Dropouts |   30   |     89.72%
|
+-------+------------------------------------------------+--------+-----------
----+
```