

Amazon_Food_Reviews_LSTM

July 8, 2019

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 - unique 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).

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 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 will 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

# importing Cross validation libs
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
from sklearn import model_selection

from matplotlib import pyplot
import seaborn as sns

import numpy
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import LSTM
from keras.layers.embeddings import Embedding
from keras.layers import BatchNormalization, Dense, Dropout, Flatten, LSTM

```

Using TensorFlow backend.

1.2 Reading Data

```
In [2]: # Code to read csv file into colaboratory:
!pip install -U -q PyDrive
from pydrive.auth import GoogleAuth
from pydrive.drive import GoogleDrive
from google.colab import auth
from oauth2client.client import GoogleCredentials

# 1. Authenticate and create the PyDrive client.
auth.authenticate_user()
gauth = GoogleAuth()
gauth.credentials = GoogleCredentials.get_application_default()
drive = GoogleDrive(gauth)

id = '1VDFn9tpw00ecnr5DiC7TQwg-GVoPJUEK'

downloaded = drive.CreateFile({'id':id})
downloaded.GetContentFile('database.sqlite')

# df2 = pd.read_csv(io.BytesIO(uploaded['Filename.csv']))

# using the 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 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 """)
# for tsne assignment you can take 5k data points

filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 LIMIT 500000 """)

# Give reviews with Score>3 a positive rating, and reviews with a score<3 a negative rating
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)
```

```
|| 993kB 5.1MB/s
Building wheel for PyDrive (setup.py) ... done
```

```
WARNING: Logging before flag parsing goes to stderr.
W0707 19:22:06.110231 140405479520128 __init__.py:44] file_cache is unavailable when using oauth2client
Traceback (most recent call last):
  File "/usr/local/lib/python3.6/dist-packages/googleapiclient/discovery_cache/__init__.py", line 1, in <module>
    from google.appengine.api import memcache
ModuleNotFoundError: No module named 'google.appengine'
```

During handling of the above exception, another exception occurred:

```
Traceback (most recent call last):
  File "/usr/local/lib/python3.6/dist-packages/googleapiclient/discovery_cache/file_cache.py", line 1, in <module>
    from oauth2client.contrib.locked_file import LockedFile
ModuleNotFoundError: No module named 'oauth2client.contrib.locked_file'
```

During handling of the above exception, another exception occurred:

```
Traceback (most recent call last):
  File "/usr/local/lib/python3.6/dist-packages/googleapiclient/discovery_cache/file_cache.py", line 1, in <module>
    from oauth2client.locked_file import LockedFile
ModuleNotFoundError: No module named 'oauth2client.locked_file'
```

During handling of the above exception, another exception occurred:

```
Traceback (most recent call last):
  File "/usr/local/lib/python3.6/dist-packages/googleapiclient/discovery_cache/__init__.py", line 1, in <module>
    from . import file_cache
  File "/usr/local/lib/python3.6/dist-packages/googleapiclient/discovery_cache/file_cache.py", line 1, in <module>
    'file_cache is unavailable when using oauth2client >= 4.0.0 or google-auth')
ImportError: file_cache is unavailable when using oauth2client >= 4.0.0 or google-auth
```

Number of data points in our data (50000, 10)

```
Out[2]:      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]
```

```
In [0]: 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	...	COUNT(*)
0	#oc-R115TNMSPFT9I7	...	2
1	#oc-R11D9D7SHXIJB9	...	3
2	#oc-R11DNU2NBKQ23Z	...	2
3	#oc-R1105J5ZVQE25C	...	3
4	#oc-R12KPBODL2B5ZD	...	2

```
[5 rows x 7 columns]
```

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

```
Out [5]:
```

	UserId	...	COUNT(*)
80638	AZY10LLTJ71NX	...	5

```
[1 rows x 7 columns]
```

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

```
Out [6]: 393063
```

2 [2] Exploratory Data Analysis

2.1 [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:

```
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	...	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]
```

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

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

```
Out[9]: (46072, 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]: 92.144
```

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 calculations

```
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    ...                               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]
```

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

```
(46071, 10)
```

```
Out[13]: 1    38479
0     7592
Name: Score, dtype: int64
```

3 [3] Preprocessing

3.1 [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 observed to be better than Porter Stemming)

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

In [0]:

```
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)
```

```
My dogs loves this chicken but its a product from China, so we wont be buying it anymore. Its
=====
this is yummy, easy and unusual. it makes a quick, delicious pie, crisp or cobbler. home made is
=====
Great flavor, low in calories, high in nutrients, high in protein! Usually protein powders are
=====
For those of you wanting a high-quality, yet affordable green tea, you should definitely give t
=====
```

```
In [15]: # 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)

```

My dogs loves this chicken but its a product from China, so we wont be buying it anymore. Its

```

In [16]: # https://stackoverflow.com/questions/16206380/python-beautifulsoup-how-to-remove-all
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)

```

My dogs loves this chicken but its a product from China, so we wont be buying it anymore. Its
=====
this is yummy, easy and unusual. it makes a quick, delicious pie, crisp or cobbler. home made is
=====
Great flavor, low in calories, high in nutrients, high in protein! Usually protein powders are
=====
For those of you wanting a high-quality, yet affordable green tea, you should definitely give t

```

In [0]: # 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]: #remove words with numbers python: https://stackoverflow.com/a/18082370/4084039
sent_0 = re.sub("\S*\d\S*", "", sent_0).strip()
print(sent_0)

```

My dogs loves this chicken but its a product from China, so we wont be buying it anymore. Its

```

In [19]: #remove spacial character: https://stackoverflow.com/a/5843547/4084039
sent_1500 = re.sub('[^A-Za-z0-9]+', ' ', sent_1500)
print(sent_1500)

```

Great flavor low in calories high in nutrients high in protein Usually protein powders are high

```

In [0]: # https://gist.github.com/sebleier/554280
# we are removing the words from the stop words list: 'no', 'nor', 'not'
# <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 reumoved in the 1st step

```

```

stopwords= set(['br', 'the', 'i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourselves',
'you'll", "you'd", 'your', 'yours', 'yourself', 'yourselves', 'he', 'him',
'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'its', 'itself', 'i',
'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this', 'that', "t",
'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have', 'has', 'ha',
'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'because', 'as',
'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into', 'through',
'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off', 'o',
'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'all', 'any',
'most', 'other', 'some', 'such', 'only', 'own', 'same', 'so', 'than', 'too',
's', 't', 'can', 'will', 'just', 'don', "don't", 'should', "should've", 'ne',
've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn', "didn't",
'hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't", 'ma', 'migh',
'mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shouldn't", 'v',
'won', "won't", 'wouldn', "wouldn't"])

```

```

In [0]: #filtered out whole reviews

```

```

from bs4 import BeautifulSoup

```

```

# Combining all the above stundents
from tqdm import tqdm
# tqdm is for printing the status bar
word_counter = []
def filterised_text(text):
    preprocessed_text = []
    for sentance in tqdm(text):
        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)
        count = len(sentance.split())
        word_counter.append(count)
        preprocessed_text.append(sentance.strip())
    return preprocessed_text

```

```

In [22]: preprocessed_reviews = filterised_text(final['Text'].values)
         final['preprocessed_reviews'] = preprocessed_reviews
         preprocessed_reviews[1822]

```

100%|| 46071/46071 [00:15<00:00, 3018.84it/s]

Out[22]: 'gobble one want dachsund mix horrible breath helps little definitely buy price right

```

In [23]: final['numbers_of_words'] = word_counter
         word_counter[1822]

```

Out[23]: 13

3.2 [3.2] Preprocessing Review Summary

```

In [24]: preprocessed_summary = filterised_text(final['Summary'].values)
         final['preprocessed_summary'] = preprocessed_summary
         preprocessed_summary[1822]

```

100%|| 46071/46071 [00:10<00:00, 4563.45it/s]

Out[24]: 'dog love'

3.2.1 Splitting data

```

In [25]: X = final['preprocessed_reviews']
         y = final['Score']

```

```

# split the data set into train and test
X_train, x_test, y_train, y_test = model_selection.train_test_split(X, y, test_size=0.2)

print(X_train.shape, x_test.shape, y_train.shape, y_test.shape)

(32249,) (13822,) (32249,) (13822,)

```

4 [4] Featurization

4.1 [4.1] Vectorize Data

In [26]: # <https://machinelearningmastery.com/prepare-text-data-deep-learning-keras/>

```

from keras.preprocessing.text import Tokenizer
from keras.preprocessing.sequence import pad_sequences

max_review_length = 500
top_words = 5000

tk = Tokenizer(lower = True, num_words= top_words)
tk.fit_on_texts(X_train)
X_train_seq = tk.texts_to_sequences(X_train)
X_train_pad = pad_sequences(X_train_seq, maxlen=max_review_length)
X_test_seq = tk.texts_to_sequences(x_test)
X_test_pad = pad_sequences(X_test_seq, maxlen=max_review_length)

print('train data shape ', X_train_pad.shape)
print('test data shape', X_test_pad.shape)

train data shape (32249, 500)
test data shape (13822, 500)

```

In [27]: # *Sequence*

```

print(X_train_seq[1])
print(type(X_train_seq[1]))
print(len(X_train_seq[1]))

[3396, 7, 34, 1, 47, 442, 58, 2, 63, 992]
<class 'list'>
10

```

In [28]: # *Padding*


```
In [29]: # create the model
        embedding_vecor_length = 64
        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
```

W0707 19:22:44.331145 140405479520128 deprecation_wrapper.py:119] From /usr/local/lib/python3.6/dist-packages/tensorflow/python/training/training_util.py:110: create_session (from tensorflow/python/training/training_util) is deprecated and will be removed in a future version. Use tf.nn.stateful_session instead.

W0707 19:22:44.362855 140405479520128 deprecation_wrapper.py:119] From /usr/local/lib/python3.6/dist-packages/tensorflow/python/training/training_util.py:110: create_session (from tensorflow/python/training/training_util) is deprecated and will be removed in a future version. Use tf.nn.stateful_session instead.

W0707 19:22:44.368639 140405479520128 deprecation_wrapper.py:119] From /usr/local/lib/python3.6/dist-packages/tensorflow/python/training/training_util.py:110: create_session (from tensorflow/python/training/training_util) is deprecated and will be removed in a future version. Use tf.nn.stateful_session instead.

W0707 19:22:44.618789 140405479520128 deprecation_wrapper.py:119] From /usr/local/lib/python3.6/dist-packages/tensorflow/python/training/training_util.py:110: create_session (from tensorflow/python/training/training_util) is deprecated and will be removed in a future version. Use tf.nn.stateful_session instead.

W0707 19:22:44.780548 140405479520128 deprecation_wrapper.py:119] From /usr/local/lib/python3.6/dist-packages/tensorflow/python/training/training_util.py:110: create_session (from tensorflow/python/training/training_util) is deprecated and will be removed in a future version. Use tf.nn.stateful_session instead.

W0707 19:22:44.786787 140405479520128 deprecation.py:323] From /usr/local/lib/python3.6/dist-packages/tensorflow/python/training/training_util.py:110: create_session (from tensorflow/python/training/training_util) is deprecated and will be removed in a future version. Use tf.nn.stateful_session instead.

Instructions for updating:

Use tf.nn.stateful_session in 2.0, which has the same broadcast rule as np.where

```
-----
Layer (type)                 Output Shape              Param #
=====
embedding_1 (Embedding)      (None, 500, 64)          320064
-----
lstm_1 (LSTM)                (None, 100)              66000
-----
dense_1 (Dense)              (None, 1)                101
=====
Total params: 386,165
Trainable params: 386,165
Non-trainable params: 0
-----
None
```

```
In [30]: model.fit(X_train_pad, y_train, nb_epoch=10, batch_size=64)
        # Final evaluation of the model
        scores = model.evaluate(X_test_pad, y_test, verbose=0)
        print("Accuracy: %.2f%%" % (scores[1]*100))
```

W0707 19:22:45.520249 140405479520128 deprecation_wrapper.py:119] From /usr/local/lib/python3.6/dist-packages/tensorflow/python/training/training_util.py:110: create_session (from tensorflow/python/training/training_util) is deprecated and will be removed in a future version. Use tf.nn.stateful_session instead.

```

Epoch 1/10
32249/32249 [=====] - 349s 11ms/step - loss: 0.2804 - acc: 0.8896
Epoch 2/10
32249/32249 [=====] - 345s 11ms/step - loss: 0.1788 - acc: 0.9327
Epoch 3/10
32249/32249 [=====] - 345s 11ms/step - loss: 0.1494 - acc: 0.9443
Epoch 4/10
32249/32249 [=====] - 345s 11ms/step - loss: 0.1251 - acc: 0.9550
Epoch 5/10
32249/32249 [=====] - 345s 11ms/step - loss: 0.1085 - acc: 0.9606
Epoch 6/10
32249/32249 [=====] - 345s 11ms/step - loss: 0.0855 - acc: 0.9706
Epoch 7/10
32249/32249 [=====] - 344s 11ms/step - loss: 0.0732 - acc: 0.9746
Epoch 8/10
32249/32249 [=====] - 345s 11ms/step - loss: 0.0607 - acc: 0.9802
Epoch 9/10
32249/32249 [=====] - 346s 11ms/step - loss: 0.0485 - acc: 0.9839
Epoch 10/10
32249/32249 [=====] - 345s 11ms/step - loss: 0.0471 - acc: 0.9843
Accuracy: 90.39%

```

6 Apply LSTM Model 2

Here slightly modifying the model, we have considered embedding vector length is 32

```

In [31]: # create the model
         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-lstm

         model.fit(X_train_pad, y_train, nb_epoch=10, batch_size=64)
         # Final evaluation of the model
         scores = model.evaluate(X_test_pad, y_test, verbose=0)
         print("Accuracy: %.2f%%" % (scores[1]*100))

```

Layer (type)	Output Shape	Param #
embedding_2 (Embedding)	(None, 500, 32)	160032
lstm_2 (LSTM)	(None, 100)	53200

```

-----
dense_2 (Dense)                (None, 1)                101
=====
Total params: 213,333
Trainable params: 213,333
Non-trainable params: 0
-----
None
Epoch 1/10
32249/32249 [=====] - 344s 11ms/step - loss: 0.2847 - acc: 0.8871
Epoch 2/10
32249/32249 [=====] - 344s 11ms/step - loss: 0.1827 - acc: 0.9311
Epoch 3/10
32249/32249 [=====] - 343s 11ms/step - loss: 0.1542 - acc: 0.9427
Epoch 4/10
32249/32249 [=====] - 343s 11ms/step - loss: 0.1375 - acc: 0.9504
Epoch 5/10
32249/32249 [=====] - 344s 11ms/step - loss: 0.1185 - acc: 0.9561
Epoch 6/10
32249/32249 [=====] - 344s 11ms/step - loss: 0.1003 - acc: 0.9649
Epoch 7/10
32249/32249 [=====] - 344s 11ms/step - loss: 0.0837 - acc: 0.9704
Epoch 8/10
32249/32249 [=====] - 344s 11ms/step - loss: 0.0686 - acc: 0.9770
Epoch 9/10
32249/32249 [=====] - 344s 11ms/step - loss: 0.0591 - acc: 0.9804
Epoch 10/10
32249/32249 [=====] - 343s 11ms/step - loss: 0.0527 - acc: 0.9826
Accuracy: 90.18%

```

7 Apply Multiple LSTM model

Here we will try to slightly different model, we will test with stacking of LSTM model.

In [32]: # <https://keras.io/getting-started/sequential-model-guide/>

```

embedding_vecor_length = 32

# create the model
model = Sequential()
model.add(Embedding(top_words+1, embedding_vecor_length, input_length=max_review_length))
model.add(LSTM(100, return_sequences=True))
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

model.fit(X_train_pad, y_train, nb_epoch=10, batch_size=64)
# Final evaluation of the model
scores = model.evaluate(X_test_pad, y_test, verbose=0)
print("Accuracy: %.2f%%" % (scores[1]*100))

```

Layer (type)	Output Shape	Param #
embedding_3 (Embedding)	(None, 500, 32)	160032
lstm_3 (LSTM)	(None, 500, 100)	53200
lstm_4 (LSTM)	(None, 100)	80400
dense_3 (Dense)	(None, 1)	101

Total params: 293,733
 Trainable params: 293,733
 Non-trainable params: 0

```

None
Epoch 1/10
32249/32249 [=====] - 690s 21ms/step - loss: 0.2745 - acc: 0.8921
Epoch 2/10
32249/32249 [=====] - 688s 21ms/step - loss: 0.1793 - acc: 0.9316
Epoch 3/10
32249/32249 [=====] - 689s 21ms/step - loss: 0.1553 - acc: 0.9429
Epoch 4/10
32249/32249 [=====] - 688s 21ms/step - loss: 0.1281 - acc: 0.9542
Epoch 5/10
32249/32249 [=====] - 688s 21ms/step - loss: 0.1039 - acc: 0.9647
Epoch 6/10
32249/32249 [=====] - 685s 21ms/step - loss: 0.0833 - acc: 0.9722
Epoch 7/10
32249/32249 [=====] - 688s 21ms/step - loss: 0.0674 - acc: 0.9779
Epoch 8/10
32249/32249 [=====] - 691s 21ms/step - loss: 0.0548 - acc: 0.9828
Epoch 9/10
32249/32249 [=====] - 698s 22ms/step - loss: 0.0419 - acc: 0.9873
Epoch 10/10
32249/32249 [=====] - 698s 22ms/step - loss: 0.0342 - acc: 0.9897
Accuracy: 90.64%

```


8 LSTM Model with different parameter

Here we have considered single LSTM model, with various input parameter like Dropout, Batch Normalization

```
In [33]: # create the model
        embedding_vecor_length = 32
        model = Sequential()
        model.add(Embedding(top_words+1, embedding_vecor_length, input_length=max_review_length))
        model.add(Dropout(0.25))
        model.add(LSTM(100))
        model.add(BatchNormalization())
        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

        model.fit(X_train_pad, y_train, nb_epoch=10, batch_size=64)
        # Final evaluation of the model
        scores = model.evaluate(X_test_pad, y_test, verbose=0)
        print("Accuracy: %.2f%%" % (scores[1]*100))
```

W0707 23:19:37.184394 140405479520128 deprecation.py:506] From /usr/local/lib/python3.6/dist-p

Instructions for updating:

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

Layer (type)	Output Shape	Param #
embedding_4 (Embedding)	(None, 500, 32)	160032
dropout_1 (Dropout)	(None, 500, 32)	0
lstm_5 (LSTM)	(None, 100)	53200
batch_normalization_1 (Batch Normalization)	(None, 100)	400
dense_4 (Dense)	(None, 1)	101

Total params: 213,733

Trainable params: 213,533

Non-trainable params: 200

None

Epoch 1/10

32249/32249 [=====] - 355s 11ms/step - loss: 0.2925 - acc: 0.8800

Epoch 2/10

32249/32249 [=====] - 354s 11ms/step - loss: 0.1860 - acc: 0.9273

```
Epoch 3/10
32249/32249 [=====] - 353s 11ms/step - loss: 0.1535 - acc: 0.9421
Epoch 4/10
32249/32249 [=====] - 354s 11ms/step - loss: 0.1272 - acc: 0.9510
Epoch 5/10
32249/32249 [=====] - 354s 11ms/step - loss: 0.1090 - acc: 0.9579
Epoch 6/10
32249/32249 [=====] - 353s 11ms/step - loss: 0.0890 - acc: 0.9664
Epoch 7/10
32249/32249 [=====] - 350s 11ms/step - loss: 0.0787 - acc: 0.9700
Epoch 8/10
32249/32249 [=====] - 350s 11ms/step - loss: 0.0673 - acc: 0.9744
Epoch 9/10
32249/32249 [=====] - 350s 11ms/step - loss: 0.0616 - acc: 0.9765
Epoch 10/10
32249/32249 [=====] - 351s 11ms/step - loss: 0.0538 - acc: 0.9798
Accuracy: 88.66%
```

9 Conclusion

We can achieve better accuracy by stacking multiple LSTMs. With single LSTM accuracy was 90.18 and by stacking the LSTM model its slightly increase 90.67.