SentimentAnalysis with LSTM

April 21, 2022

Sentiment Analysis on Women Closthing Reviews using LSTM and Keras Project resource is from Mount San Antonio College, CISD62 by Angel Hernandez,

[ ]:
```
# data / visualization libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# nlp libraries
import re
import string
from string import punctuation
import nltk
from nltk.corpus import stopwords   # to get collection of stopwords
nltk.download('stopwords') # download stopwords

# ml libraries
import tensorflow as tf
from tensorflow.keras.datasets import imdb
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.preprocessing.text import Tokenizer  # to encode text to␣
 ↪int
from tensorflow.keras.preprocessing import sequence
from sklearn.model_selection import train_test_split
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, LSTM, Embedding
from tensorflow.keras.callbacks import ModelCheckpoint   # save model
from tensorflow.keras.models import load_model   # load saved model

data = pd.read_csv("data\women_clothing_review.csv")
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\Gumo\AppData\Roaming\nltk_data…
[nltk_data]   Package stopwords is already up-to-date!
```

[ ]:
```
data.tail()
```

[ ]:
```
       Unnamed: 0  Clothing ID  Age  \
23481       23481         1104   34
23482       23482          862   48
23483       23483         1104   31
23484       23484         1084   28
23485       23485         1104   52

                                                 Title  \
23481                     Great dress for many occasions
23482                         Wish it was made of cotton
23483                              Cute, but see through
23484  Very cute dress, perfect for summer parties an…
23485                     Please make more like this one!

                                           Review Text  Rating  \
23481  I was very happy to snag this dress at such a …       5
23482  It reminds me of maternity clothes. soft, stre…       3
23483  This fit well, but the top was very see throug…       3
23484  I bought this dress for a wedding i have this …       3
23485  This dress in a lovely platinum is feminine an…       5

       Recommended IND  Positive Feedback Count   Division Name  \
23481                1                        0  General Petite
23482                1                        0  General Petite
23483                0                        1  General Petite
23484                1                        2         General
23485                1                       22  General Petite

      Department Name Class Name
23481         Dresses    Dresses
23482            Tops      Knits
23483         Dresses    Dresses
23484         Dresses    Dresses
23485         Dresses    Dresses
```

[ ]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 23486 entries, 0 to 23485
Data columns (total 11 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   Unnamed: 0               23486 non-null  int64
 1   Clothing ID              23486 non-null  int64
 2   Age                      23486 non-null  int64
 3   Title                    19676 non-null  object
 4   Review Text              22641 non-null  object
 5   Rating                   23486 non-null  int64
```

```
 6   Recommended IND          23486 non-null  int64
 7   Positive Feedback Count  23486 non-null  int64
 8   Division Name            23472 non-null  object
 9   Department Name          23472 non-null  object
 10  Class Name               23472 non-null  object
dtypes: int64(6), object(5)
memory usage: 2.0+ MB
```

[ ]:
```
# drop coloumns
data = data.drop(columns=["Unnamed: 0", "Title", "Positive Feedback Count"],
 ↪axis=1)
data.dropna(inplace=True)
```

[ ]:
```
data.head()
```

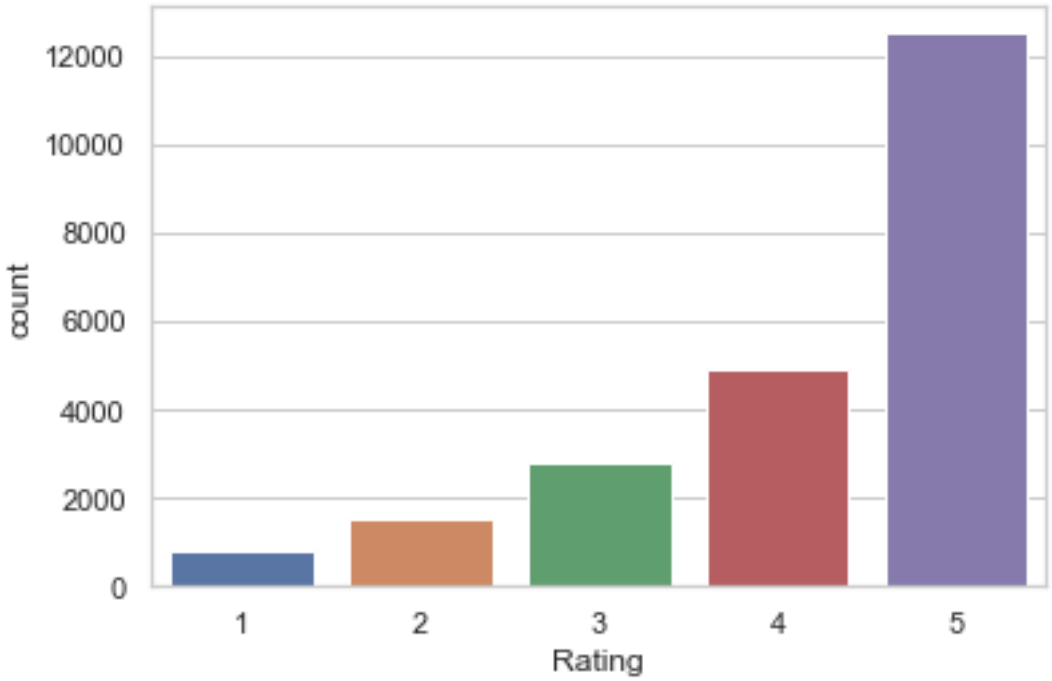
[ ]:
```
   Clothing ID  Age                                        Review Text  \
0          767   33  Absolutely wonderful - silky and sexy and comf…
1         1080   34  Love this dress!  it's sooo pretty.  i happene…
2         1077   60  I had such high hopes for this dress and reall…
3         1049   50  I love, love, love this jumpsuit. it's fun, fl…
4          847   47  This shirt is very flattering to all due to th…

   Rating  Recommended IND   Division Name Department Name Class Name
0       4                1       Initmates        Intimate  Intimates
1       5                1         General         Dresses    Dresses
2       3                0         General         Dresses    Dresses
3       5                1  General Petite         Bottoms      Pants
4       5                1         General            Tops    Blouses
```

[ ]:
```
data['Polarity_Rating'] = data['Rating'].apply(lambda x: 'Positive' if x > 3
 ↪else 'Negative')
```

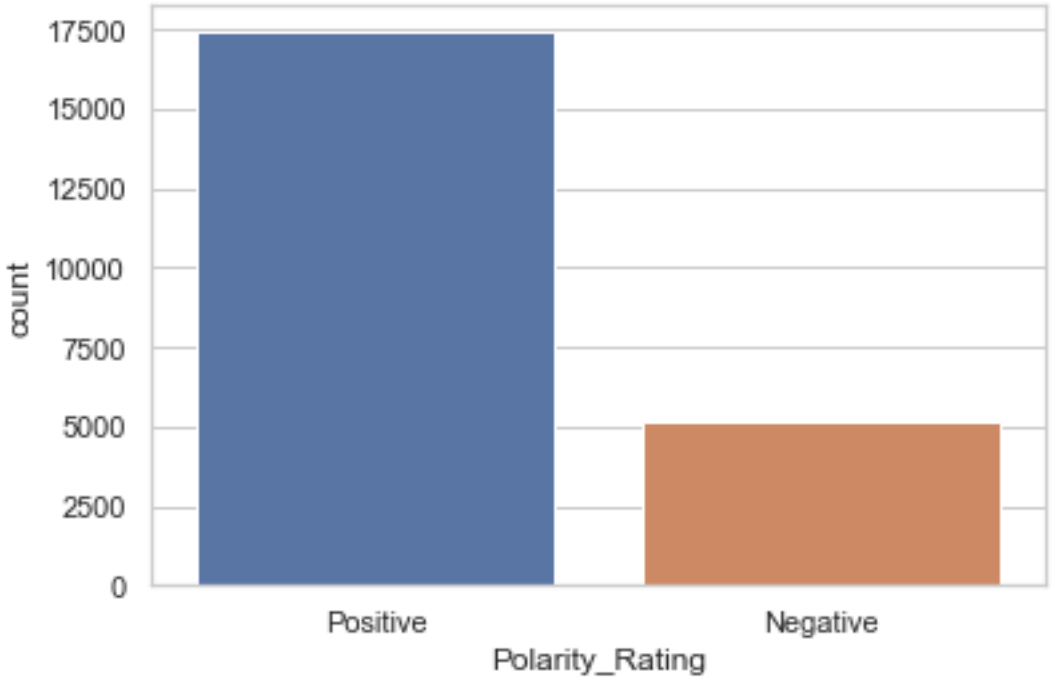
[ ]:
```
# countplot of ratings
sns.set_theme(style="whitegrid")
sns.countplot(x=data.Rating)
```

[ ]:
```
<AxesSubplot:xlabel='Rating', ylabel='count'>
```



[ ]:
```
#countplot ploarity
sns.countplot(x=data.Polarity_Rating)
```

[ ]:
```
<AxesSubplot:xlabel='Polarity_Rating', ylabel='count'>
```



[ ]:
```
data_Positive = data[data['Polarity_Rating'] == 'Positive'][0:8000]
data_Negative = data[data['Polarity_Rating'] == 'Negative']
```

[ ]:
```
# since we dont have enough data for "Negative",
#  we produce more "Negative" to meet the 8000 sample size by copy paste them

data_Negative_over = data_Negative.sample(8000, replace=True)
data = pd.concat([data_Positive, data_Negative_over], axis=0)
```

[ ]:
```
# removing stop words
def get_text_processing(text):
    stpword = stopwords.words('english')

    # remove the word not from stop word
    stpword.remove('not')
    no_punctuation = [char for char in text if char not in string.punctuation]
    no_punctuation = ''.join(no_punctuation)
    return ' '.join([word for word in no_punctuation.split() if word.lower()␣
 ↪not in stpword])
```

[ ]:
```
# remove stop wrod in review
data['review'] = data['Review Text'].apply(get_text_processing)
```

[ ]:
```
data.head()
```

[ ]:

	Clothing ID	Age	Review Text	Rating	Recommended IND	Division Name	Department Name	Class Name	Polarity_Rating	review
0	767	33	Absolutely wonderful - silky and sexy and comf…	4	1	Initmates	Intimate	Intimates	Positive	Absolutely wonderful silky sexy comfortable
1	1080	34	Love this dress! it's sooo pretty. i happene…	5	1	General	Dresses	Dresses	Positive	Love dress sooo pretty happened find store im …
3	1049	50	I love, love, love this jumpsuit. it's fun, fl…	5	1	General Petite	Bottoms	Pants	Positive	love love love jumpsuit fun flirty fabulous ev…
4	847	47	This shirt is very flattering to all due to th…	5	1	General	Tops	Blouses	Positive	shirt flattering due adjustable front tie perf…
6	858	39	I aded this in my basket at hte last mintue to…	5	1	General Petite	Tops	Knits	Positive	aded basket hte last mintue see would look lik…

[ ]:
```
data = data[['review', 'Polarity_Rating']]
```

[ ]:
```
data.head()
```

[ ]:

	review	Polarity_Rating
0	Absolutely wonderful silky sexy comfortable	Positive
1	Love dress sooo pretty happened find store im …	Positive
3	love love love jumpsuit fun flirty fabulous ev…	Positive
4	shirt flattering due adjustable front tie perf…	Positive
6	aded basket hte last mintue see would look lik…	Positive

[ ]:
```
english_stops = set(stopwords.words('english'))
english_stops.remove('not')
```

[ ]:
```
def load_dataset(txt):
    #df = pd.read_csv('IMDB Dataset.csv')
    df = txt
    x_data = df['review']       # Reviews/Input
    y_data = df['Polarity_Rating']    # Sentiment/Output

    # PRE-PROCESS REVIEW
    x_data = x_data.replace({'<.*?>': ''}, regex = True)          # remove html tag
    x_data = x_data.replace({'[^A-Za-z]': ' '}, regex = True)     # remove non alphabet
    x_data = x_data.apply(lambda review: [w for w in review.split() if w not in english_stops])  # remove stop words
    x_data = x_data.apply(lambda review: [w.lower() for w in review])   # lower case

    # ENCODE SENTIMENT -> 0 & 1
    y_data = y_data.replace('Positive', 1)
    y_data = y_data.replace('Negative', 0)


    return x_data, y_data
```

[ ]:
```
x_data, y_data = load_dataset(data)
print('Reviews')
print(x_data, '\n')
print('Sentiment')
print(y_data)
```

```
Reviews
0        [absolutely, wonderful, silky, sexy, comfortable]
1        [love, dress, sooo, pretty, happened, find, st…
3        [love, love, love, jumpsuit, fun, flirty, fabu…
4        [shirt, flattering, due, adjustable, front, ti…
```

```
6        [aded, basket, hte, last, mintue, see, would, …
                                ⋮
11381    [vest, nice, fashionable, stylish, like, lot, …
5697     [love, cold, shoulder, trend, top, seemed, sat…
19340    [skirt, fits, strange, way, one, pleated, area…
5072     [top, really, cute, threads, underneath, shirt…
7773     [super, cute, colors, vibrant, thin, enough, w…
Name: review, Length: 16000, dtype: object

Sentiment
0        1
1        1
3        1
4        1
6        1
        ..
11381    0
5697     0
19340    0
5072     0
7773     0
Name: Polarity_Rating, Length: 16000, dtype: int64
```

[ ]:
```
X_train, X_test, y_train, y_test = train_test_split(x_data, y_data, test_size=0.
↪2, random_state=42)
```

[ ]:
```
print(X_train)
print(X_test)
print(y_train)
print(y_test)
```

```
923      [really, loved, soft, snuggly, unsure, orderin…
3759     [dress, runs, large, lbs, hourglass, curvy, bu…
9495                    [dress, pretty, neckline, darling]
16491    [beautifully, made, shirt, however, sizing, wa…
15758    [large, looked, awful, huge, armholes, baggy, …
                                ⋮
2874     [order, retailer, regularly, pretty, consisten…
7179     [really, wanted, love, dress, like, lacing, ne…
1169     [although, may, not, look, like, takes, shape,…
17322    [pants, fit, tts, ask, pictured, length, go, t…
9781     [got, teal, color, beautiful, get, many, compl…
Name: review, Length: 12800, dtype: object
4096     [well, disappointed, fabric, dress, heavier, m…
6246     [love, bulging, substantive, fabric, flatterin…
8143     [bought, whim, gift, mom, fit, perfectly, love…
413      [got, green, color, gray, accent, stitching, l…
11803    [saw, dress, online, thought, perfectly, cute,…
```

```
                                   …
9594     [hoped, bulky, knit, would, cuddly, soft, suri…
7654     [fabric, beautiful, embroidery, quite, strikin…
8550     [brand, makes, best, jackets, got, vest, last,…
10256    [first, saw, online, worried, design, might, l…
13909    [sweater, pretty, short, beyond, raised, arms,…
Name: review, Length: 3200, dtype: object
923      1
3759     0
9495     1
16491    0
15758    0
        ..
2874     0
7179     1
1169     1
17322    0
9781     1
Name: Polarity_Rating, Length: 12800, dtype: int64
4096     0
6246     1
8143     1
413      1
11803    0
        ..
9594     0
7654     1
8550     1
10256    1
13909    0
Name: Polarity_Rating, Length: 3200, dtype: int64
```

[ ]:
```python
# Max length of review
def get_max_length():
    review_length = []
    for review in X_train:
        review_length.append(len(review))

    return int(np.ceil(np.mean(review_length)))
```

[ ]:
```python
max_length = get_max_length()
print(max_length)
```

```
30
```

[ ]:
```python
# ENCODE REVIEW
token = Tokenizer(lower=False)    # False becuase we already did it.
```

```
# find formula to vectorize the text
token.fit_on_texts(X_train)

# converting text into integer
x_train = token.texts_to_sequences(X_train)
x_test = token.texts_to_sequences(X_test)

### this is the code to add the pad to x_train
x_train = pad_sequences(x_train, maxlen=max_length, padding='post',␣
 ↪truncating='post')

############## add pad to x_test   ############################
x_test = pad_sequences(x_test, maxlen=max_length, padding='post',␣
 ↪truncating='post')

total_words = len(token.word_index) + 1   # we need to add 1 because of 0␣
 ↪padding
```

[ ]:
```
print(x_train)
print(x_test)
print(max_length)
```

```
[[  16   81   33 …    0    0    0]
 [   2   80   26 …    8  418    7]
 [   2   45  223 …    0    0    0]
 …
 [ 346  176    1 …    0    0    0]
 [  71    7  261 …   43   93  233]
 [  50 1412   15 …    0    0    0]]
[[  30  121   11 …    0    0    0]
 [   6 6927   11 … 1777   11 4173]
 [  36 1202 1228 …    0    0    0]
 …
 [ 354  130  314 …  367  134  262]
 [ 100  139   74 …   50   59    1]
 [  37   45   54 …    0    0    0]]
30
```

[ ]:
```
# ARCHITECTURE
EMBED_DIM = 32
LSTM_OUT = 64

#### add the model here:
model = Sequential()
model.add(Embedding(input_dim=total_words, output_dim=128,
                    input_length=max_length))
```

```
# dropout and recurrent dropout
model.add(LSTM(units=128, dropout=0.2, recurrent_dropout=0.2))
model.add(Dense(units=1, activation='sigmoid'))

### compile the model using: optimizer = 'adam', loss = 'binary_crossentropy',␣
 ↪metrics = ['accuracy']
model.compile(optimizer='adam', loss='binary_crossentropy',␣
 ↪metrics=['accuracy'])
```

[ ]:
```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding (Embedding)       (None, 30, 128)           1522944

 lstm (LSTM)                 (None, 128)               131584

 dense (Dense)               (None, 1)                 129

=================================================================
Total params: 1,654,657
Trainable params: 1,654,657
Non-trainable params: 0
_________________________________________________________________
```

[ ]:
```
# Save model checkpoint and save best only
checkpoint = ModelCheckpoint('models/LSTM.h5', monitor='accuracy',␣
 ↪save_best_only=True, verbose=1)
```

[ ]:
```
# fit and train model, call back based on checkpoint(best model)
history = model.fit(x_train, y_train, epochs=10, batch_size=32,␣
 ↪validation_data=(x_test, y_test), callbacks=[checkpoint])
```

```
Epoch 1/10
400/400 [==============================] - ETA: 0s - loss: 0.4133 - accuracy:
0.8126
Epoch 1: accuracy improved from -inf to 0.81258, saving model to models\LSTM.h5
400/400 [==============================] - 19s 42ms/step - loss: 0.4133 -
accuracy: 0.8126 - val_loss: 0.3370 - val_accuracy: 0.8669
Epoch 2/10
400/400 [==============================] - ETA: 0s - loss: 0.2527 - accuracy:
0.9052
Epoch 2: accuracy improved from 0.81258 to 0.90523, saving model to
models\LSTM.h5
400/400 [==============================] - 20s 50ms/step - loss: 0.2527 -
accuracy: 0.9052 - val_loss: 0.3176 - val_accuracy: 0.8744
```

```
Epoch 3/10
399/400 [============================>.] - ETA: 0s - loss: 0.1802 - accuracy:
0.9354
Epoch 3: accuracy improved from 0.90523 to 0.93547, saving model to
models\LSTM.h5
400/400 [==============================] - 19s 48ms/step - loss: 0.1801 -
accuracy: 0.9355 - val_loss: 0.4249 - val_accuracy: 0.8716
Epoch 4/10
400/400 [==============================] - ETA: 0s - loss: 0.1283 - accuracy:
0.9555
Epoch 4: accuracy improved from 0.93547 to 0.95547, saving model to
models\LSTM.h5
400/400 [==============================] - 19s 48ms/step - loss: 0.1283 -
accuracy: 0.9555 - val_loss: 0.3357 - val_accuracy: 0.8750
Epoch 5/10
399/400 [============================>.] - ETA: 0s - loss: 0.0877 - accuracy:
0.9715
Epoch 5: accuracy improved from 0.95547 to 0.97141, saving model to
models\LSTM.h5
400/400 [==============================] - 18s 45ms/step - loss: 0.0879 -
accuracy: 0.9714 - val_loss: 0.3590 - val_accuracy: 0.8841
Epoch 6/10
399/400 [============================>.] - ETA: 0s - loss: 0.0745 - accuracy:
0.9764
Epoch 6: accuracy improved from 0.97141 to 0.97648, saving model to
models\LSTM.h5
400/400 [==============================] - 19s 46ms/step - loss: 0.0744 -
accuracy: 0.9765 - val_loss: 0.3974 - val_accuracy: 0.8722
Epoch 7/10
400/400 [==============================] - ETA: 0s - loss: 0.0669 - accuracy:
0.9778
Epoch 7: accuracy improved from 0.97648 to 0.97781, saving model to
models\LSTM.h5
400/400 [==============================] - 19s 47ms/step - loss: 0.0669 -
accuracy: 0.9778 - val_loss: 0.4238 - val_accuracy: 0.8725
Epoch 8/10
399/400 [============================>.] - ETA: 0s - loss: 0.0482 - accuracy:
0.9837
Epoch 8: accuracy improved from 0.97781 to 0.98367, saving model to
models\LSTM.h5
400/400 [==============================] - 19s 47ms/step - loss: 0.0483 -
accuracy: 0.9837 - val_loss: 0.4934 - val_accuracy: 0.8772
Epoch 9/10
399/400 [============================>.] - ETA: 0s - loss: 0.0383 - accuracy:
0.9882
Epoch 9: accuracy improved from 0.98367 to 0.98820, saving model to
models\LSTM.h5
400/400 [==============================] - 19s 48ms/step - loss: 0.0382 -
```

```
accuracy: 0.9882 - val_loss: 0.4927 - val_accuracy: 0.8669
Epoch 10/10
400/400 [==============================] - ETA: 0s - loss: 0.0305 - accuracy:
0.9910
Epoch 10: accuracy improved from 0.98820 to 0.99102, saving model to
models\LSTM.h5
400/400 [==============================] - 20s 49ms/step - loss: 0.0305 -
accuracy: 0.9910 - val_loss: 0.5060 - val_accuracy: 0.8700
```

[ ]:
```
# Load the best model saved
loaded_model = tf.keras.models.load_model('models/LSTM.h5')
```

[ ]:
```
review = str(input('Clothing review: '))
```

[ ]:
```
# Pre-process input
regex = re.compile(r'[^a-zA-Z\s]')
review = regex.sub('', review)
print('Cleaned: ', review)

# remove stop word for input
words = review.split(' ')
filtered = [w for w in words if w not in english_stops]
filtered = ' '.join(filtered)
filtered = [filtered.lower()]

print('Filtered: ', filtered)
```

```
Cleaned:
Filtered:  ['']
```

[ ]:
```
# tokenize the filtered word
tokenize_words = token.texts_to_sequences(filtered)

# apply padding
tokenize_words = pad_sequences(tokenize_words, maxlen=max_length,␣
 ↪padding='post', truncating='post')
print(tokenize_words)
```

```
[[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]]
```

[ ]:
```
# use the best model to predict
result = loaded_model.predict(tokenize_words)
print(result)
```

```
[[0.69847417]]
```

[ ]:
```
# Note the result is 0 to 1
if result < 0.5:
    print('negative')
```

```
else:
    print('postive')
```

```
postive
```