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Sentiment Analysis Using Neural Networks

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Abstract: ***The advent of machine learning and artificial intelligence (AI) has be0stowed a significant advantage upon businesses, particularly through the analysis of Amazon reviews. As Amazon has become almost synonymous with online shopping, it has empowered small businesses to grow more rapidly than through conventional retail channels. This platform eases self-publishing, enabling individuals to distribute their books without needing to secure a publisher. Additionally, it allows small enterprises, irrespective of their location, to set up an Amazon account and reach a global customer base. This paper explores how machine learning and AI enhance the utility of Amazon review analysis, providing businesses with critical insights to drive growth and improve customer satisfaction.***

Keywords: Sentiment Analysis, Neural Networks, ML, AI

1. Introduction

Machine learning and AI have provided businesses with a priceless advantage: Amazon review analysis.

Amazon and online shopping have become synonymous, owing to the platform's ability to allow small businesses to expand faster than they could through traditional retail outlets. A person can self-publish a copy of the book without having to worry about convincing a publisher. A small business in a faraway land can open an Amazon account and sell to people all over the world.

Because of its prominence and popularity, Amazon is the only site where people genuinely spend time and give lengthy evaluations, as opposed to other platforms where customers must be prodded. As the case we will look at later shows, Amazon review research process can reveal a lot about a product, including aspects that the company may not have considered.

a) Analytical Question:

Analyzing Amazon review data can provide valuable customer response that can be used to improve products? Discover product features from Amazon reviews while also allowing brands to explore beyond star ratings. The sentimental analysis method will be used to solve this analysis.

b) Goals and Objectives:

Understanding consumer behavior and demands in relation to a company and its products is critical. Sentiment analysis is one of the main aspects in which NLP has been widely applied. In general, client feedback on a product can be classified as Positive, Negative, or Neutral. Companies can decide how satisfied their clients are with their products/services by interpreting client feedback through product reviews.

c) Sentimental Analysis:

Many of us, without even realizing it, engage in sentiment analysis on a regular basis. It has become a fundamental part of our culture; from the reviews we post on sites like Yelp and Amazon to the comments we provide on a purchase in an online store. Companies had huge difficulty early on with how to respond to often contradictory customer feedback. Companies were able to deal with this issue thanks to the emergence of sentiment analysis, which allowed them to focus on the overall tone of the remarks rather than the specifics and change their responses accordingly.

Finding the emotions underlying each phrase - whether anger, contempt, fear, joy, sadness, or surprise - is a typical method. NLP, which evaluates the meaning of each word, is used to do this. Following that, machine learning and natural language comprehension are used to figure out what the text is about, such as what generated the feelings or how they are related to one another.

Sentimental Analysis classified into three categories:

- Predictive sentiment analysis
- Diagnostic sentiment analysis
- Sentiment classification

In this analysis, we used Recurrent Neural Network (RNN), A recurrent neural network is a type of neural network that is designed to handle a sequence of data x(t)= x(1), x(2),..., x() with a time step index t ranging from 1 to t. RNNs are often preferable for jobs that need sequential inputs, such as voice and language. RNNs are referred to as recurrent because they do the same task for each element of a sequence, with the outcome relying on past calculations. If you wish to expect the next word in a sentence in an NLP problem, you must first understand the words that precede it. RNNs also have a "memory" that stores information about earlier calculations.
In RNN, the sequence we are interested in is a three-word sentence, the network will be unrolled into a three-layer neural network, with one layer for each word.

- Input: At time step t, x(t) is used as the network's input. For instance, x1 could be a one-hot vector matching a sentence's first word.
- Hidden state: h(t) is a hidden state at time t and serves as the network's "memory." h(t) is calculated using the current input and the hidden state from the earlier time step: h(t) = f (U x(t) + W h(t1)). A non-linear transformation, such as tanh or ReLU, is assumed for the function f.
- Weights: The RNN has input to hidden connections that are measured by a weight matrix U, hidden-to-hidden recurrent connections that are measured by a weight matrix W, and hidden-to-output connections that are

parameterized by a weight matrix V, with all of these weights (U,V,W) being shared across time.
- Output: The output of the network is represented by o(t). In the diagram, I simply added an arrow after o(t), which is likewise prone to non-linearity, particularly when the network has further layered downstream.

We use RNN with LSTM models for this analysis.

2. Data Objectives

Do the following to prove the Data cleaning process:

2.1 EDA is explained as follows:

Exploratory data analysis explores a series of stages and processes that involve data preparation and cleaning to obtain clean data set. Lemmatizing, tokenization, and the removal of unclean data (tags, punctuation, stop words, and so on) were conducted in addition to the fundamental preprocessing and data cleaning had done to the text data. This alone resulted in an increase of over 18 points in accuracy. and visually plot the data. EDA has not changed.

Changes to the hyperparameters of all evaluated models to enhance accuracy even slightly, inclusion of cross validation testing for all models, and an increase in dataset size are the primary differences of work.

We must assume that all customers who buy a product leave a rating/review to find genuine general sentiment toward the product. In practice, this is not the case. Most people who buy a product do not give it a review or a rating. The expectation is that the bulk of evaluations will be on either extreme, but it turns out that follow-up emails and marketing for a product can result in various reviews ranging from ordinary (3 stars) to exceptional (5 stars). When someone is writing a piece critiquing a product, on the other hand, the length of a text review is usually longer. Our EDA proves this, and the dataset itself has a positive bias.

- The first stage is to check for duplicates, missing values, and data that is inconsistent.
- We estimate the importance of columns and drop/keep them as needed, mostly keeping only text data.
- Because the number of rows having NANs was so little in comparison to the overall number of rows, we decided to remove them.
- The overall column (i.e., product rating) and the review column are the two key columns on which we focus our investigation. column of text (i.e., textual description and product review).
- Punctuation Elimination, the removal of redundant and special characters, such as punctuation, is a key duty in text normalization. The fundamental reason for this is that, while punctuation can offer useful insights into a review's emotion, even advanced language processing models such as BERT and GPT3 are unable to detect it. Because punctuation tends to throw the models off rather than aiding them in predicting the correct class, cutting it is a popular approach.
- Num_words_text is removed, Num_words_text are the words that appear the most often when a corpus of text is aggregated based on solitary tokens and their frequencies are examined. Num_words_text include articles (a, the, and an), pronouns (you, them, they, me), and prepositions. They are insignificant at best. They are often eliminated from text during processing to preserve words with the most meaning and context.
- Stemming and lemmatization, Lemmatization is the process of reducing each word's inflectional forms to a single base or root. Stemming is a crude method that chops off the ends of words in the hopes of reaching this goal most of the time, and it sometimes includes the removal of word formation units (the resulting part is known as the stem). Lemmatization is the process of returning the bottom or vocabulary of a word, that is known as the lemma, by appropriately using a vocabulary and morphological study of words.

Because the text is the least structured of all the access data, it has many sorts of noise and is unusable without pre-processing. Text preprocessing refers to the process of cleaning and standardizing text to make it noise-free and ready for analysis. It is needed to obtain any coherent results.

2.2 Process of Tokenization:

Tokenization is the process of dividing or tokenizing a string of text into a list of tokens. Tokens are subunits of text document parts. They can be words, sentences, or phrases, among other things. For tokenization, we employed the Ngrams approach in our study. An n-gram is a contiguous sequence of n items from a text or audio sample, syllables, Phonemes, letters, words, and base pairs are common objects, depending on the appliance.

Tokenizer.sequences to matrix (x, mode='binary'): X = tokenizer.sequences to matrix (x, mode= If the word is present in the sample, the value of a word feature is 1, otherwise it is zero.

Count: X = tokenizer.sequences to matrix (x, mode='count'); the value is the number of times a word appears in the phrase in this example.

Tokenizer.sequences to matrix (x, mode='tfidf'): TF-IDF: X = tokenizer.sequences to matrix (x, mode= In this case, we analyze the TF and IDF of the sample word in relation to the word's occurrence across the document.

2.3 Process of padding

In the padding process, each word is equal to a vector, each sample with a different number of words will have a different number of vectors. Now, to feed a model, each sample must have the same dimension, which needs padding to ensure that the number of words in each sample is equal.
Each text is converted into an integer sequence. In other words, if you had a sentence, it would assign an integer to each word in it. To confirm the given integer to your word,

use tokenizer.word index () (returns a dictionary). We are padding all sentences to a maximum length of 100 characters.

2.4 Finding Sentiments

In this analysis, we used Recurrent neural network with LSTM model with sentiment processing and an embedding approach. The sentiments are categorized "Positive," "Neutral" and "Negative," "Overall" column has 1 to 5 ratings with Review text. "4 and 5" were Positive, 3 – Neutral and 1 and 2 were Negative" to get sentiment in out model, we created a simple method to get sentiments from overall reviews, basically "3, 4 and 5" rating is Positive and anything below which is "1 and 2: are considered "Negative". Accuracy, a basic calculation of the percent of accurately predicted labels, was used as the loss metric. Even with sentiment partitioning, the model accuracy on the test set never exceeded 56 percent, while approaching train accuracy.

2.5 Data Preparation

For this Sentimental analysis, we are using UCI data set from UCI Machine Learning Repository. This data set has 3000 records with positive and negative sentiment available from 3 different websites: Amazon, IMDb, and Yelp. 500 positive sentences are labeled 1 and 500 negative sentences are labeled 0. Each website's information is saved in a separate text file.

1) Include standard imports and creating data frames:

```
import matplotlib as mpl
import matplotlib.pyplot as plt
import os
import re
import shutil
import string
import tensorflow as tf
from tensorflow.keras import regularizers
from tensorflow.keras import layers
from tensorflow.keras import losses
from collections import Counter
from nltk.corpus import stopwords

import pandas as pd
import numpy as np

import sklearn

from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report
from tensorflow.keras import preprocessing
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences

import seaborn as sns
import pydot
```

2) Loaded the data set into pandas:

```
review_data = pd.read_csv('C:/Kailash/Rekha/D213/Task2/Beauty_5.csv')
print(review_data.head(10))
```

```
      reviewerID        asin title                   reviewerName helpful  \
0  A1YJEY40YUW4SE  7806397051   NaN                        Andrea  [3, 4]
1    A60XNB876KYML  7806397051   NaN                  Jessica H.  [1, 1]
2  A3G6XNM240RMWA  7806397051   NaN                       Karen  [0, 1]
3  A1PQFP6SAJ6D80  7806397051   NaN                       Norah  [2, 2]
4  A38FVHZTNQ271F  7806397051   NaN                  Nova Amor  [0, 0]
5  A3BTN14HIZET6Z  7806397051   NaN  S. M. Randall "WildHorseWoman"  [1, 2]
6  A1Z59RFKN0M5QL  7806397051   NaN              tasha "luvely12b"  [1, 3]
7   AWUO9P6PL1SY8  7806397051   NaN                  TreMagnifique  [0, 1]
8  A3LMILRM9OC3SA  9759091062   NaN                            NaN  [0, 0]
9  A30IP88QK3YUIO  9759091062   NaN            Amina Bint Ibraheem  [0, 0]

                                  reviewText  overall  \
0  Very oily and creamy. Not at all what I expect...      1.0
1  This palette was a decent price and I was look...      3.0
2  The texture of this concealer pallet is fantas...      4.0
3  I really can't tell what exactly this thing is...      2.0
4  It was a little smaller than I expected, but t...      3.0
5  I was very happy to get this palette, now I wi...      5.0
6  PLEASE DONT DO IT! this just rachett the palet...      1.0
7  Chalky,Not Pigmented,Wears off easily,Not a Co...      2.0
8  Did nothing for me. Stings when I put it on. I...      2.0
9  I bought this product to get rid of the dark s...      3.0
```

3) Loaded the data set into data frames:

```
                                                summary unixReviewTime  \
0                                   Don't waste your money      1391040000
1                                             OK Palette!      1397779200
2                                           great quality      1378425600
3                                   Do not work on my face      1386460800
4                                             It's okay.       1382140800
5                                        Very nice palette!      1365984000
6                                                  smh!!!       1376611200
7  Chalky, Not Pigmented, Wears off easily, Not a...      1378252800
8        no Lightening, no Brightening,.....NOTHING       1405209600
9                                           Its alright       1388102400

    reviewTime  Unnamed: 10
0  01 30, 2014          NaN
1  04 18, 2014          NaN
2   09 6, 2013          NaN
3   12 8, 2013          NaN
4  10 19, 2013          NaN
5  04 15, 2013          NaN
6  08 16, 2013          NaN
7   09 4, 2013          NaN
8  07 13, 2014          NaN
9  12 27, 2013          NaN
```

4) Examine the Amazon data frames and checking their dimensions:

```
print(review_data.head(10))
print(len(review_data))
print('Unique Products')
print(len(review_data.groupby('asin')))
print('Unique Users')
print(len(review_data.groupby('reviewerID')))
```

```
       reviewerID        asin title                   reviewerName helpful  \
0  A1YJEY40YUW4SE  7806397051   NaN                        Andrea  [3, 4]
1    A60XNB876KYML  7806397051   NaN                  Jessica H.  [1, 1]
2  A3G6XNM240RMWA  7806397051   NaN                       Karen  [0, 1]
3  A1PQFP6SAJ6D80  7806397051   NaN                       Norah  [2, 2]
4  A38FVHZTNQ271F  7806397051   NaN                  Nova Amor  [0, 0]
5  A3BTN14HIZET6Z  7806397051   NaN  S. M. Randall "WildHorseWoman"  [1, 2]
6  A1Z59RFKN0M5QL  7806397051   NaN              tasha "luvely12b"  [1, 3]
7   AWUO9P6PL1SY8  7806397051   NaN                  TreMagnifique  [0, 1]
8  A3LMILRM9OC3SA  9759091062   NaN                            NaN  [0, 0]
9  A30IP88QK3YUIO  9759091062   NaN            Amina Bint Ibraheem  [0, 0]

                                  reviewText  overall  \
0  Very oily and creamy. Not at all what I expect...      1.0
1  This palette was a decent price and I was look...      3.0
2  The texture of this concealer pallet is fantas...      4.0
3  I really can't tell what exactly this thing is...      2.0
4  It was a little smaller than I expected, but t...      3.0
5  I was very happy to get this palette, now I wi...      5.0
6  PLEASE DONT DO IT! this just rachett the palet...      1.0
7  Chalky,Not Pigmented,Wears off easily,Not a Co...      2.0
8  Did nothing for me. Stings when I put it on. I...      2.0
9  I bought this product to get rid of the dark s...      3.0

                                                summary unixReviewTime  \
0                                   Don't waste your money      1391040000
1                                             OK Palette!      1397779200
2                                           great quality      1378425600
3                                   Do not work on my face      1386460800
4                                             It's okay.       1382140800
5                                        Very nice palette!      1365984000
6                                                  smh!!!       1376611200
7  Chalky, Not Pigmented, Wears off easily, Not a...      1378252800
8        no Lightening, no Brightening,.....NOTHING       1405209600
9                                           Its alright       1388102400
```

5) Clean the data set using clean_text function:

```
review_data['reviewText'] = review_data['reviewText'].fillna("")

#review_data['reviewText'] = review_data['reviewText'].apply(remove_url)
review_data['reviewText'] = review_data['reviewText'].apply(clean_text)
review_data['Num_words_text'] = review_data['reviewText'].apply(lambda x:len(str(x).split()))

print('-------Dataset --------')
print(review_data['overall'].value_counts())
print(len(review_data))
print('-------------------------')
max_review_data_sentence_length  = review_data['Num_words_text'].max()

print('Train Max Sentence Length :'+str(max_review_data_sentence_length))
```

```
-------Dataset --------
5.0    98029
4.0    34131
3.0    19049
2.0     9845
1.0     8948
0.0        1
Name: overall, dtype: int64
198502
-------------------------
Train Max Sentence Length :2033
```

6) Include descriptive statistics feature:

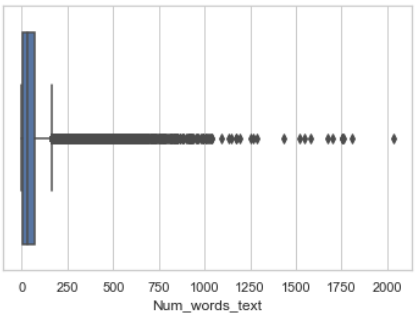
```
review_data['Num_words_text'].describe()
```

```
count    198502.000000
mean         51.349634
std          67.989213
min           0.000000
25%           4.000000
50%          31.000000
75%          69.000000
max        2033.000000
Name: Num_words_text, dtype: float64
```

7) Plot the sns:

```
    sns.set(style="whitegrid")
    sns.boxplot(x=review_data['Num_words_text'])
```

```
<AxesSubplot:xlabel='Num_words_text'>
```



8) Include the short reviews and long reviews:

```
mask = (review_data['Num_words_text'] < 100) & (review_data['Num_words_text'] >=20)
df_short_reviews = review_data[mask]
print('No of Short reviews')
print(len(df_short_reviews))

mask = review_data['Num_words_text'] >= 100
df_long_reviews = review_data[mask]
print('No of Long reviews')
print(len(df_long_reviews))
```

```
No of Short reviews
99900
No of Long reviews
29478
```

9) Print the Short reviews:

```
print(df_short_reviews['Num_words_text'].max())
```

```
99
```

10) Split data set into train and test:

```
#df_short_reviews['rating'].value_counts()
filtered_data = df_short_reviews.groupby('asin').filter(lambda x: len(x) >= 20)
print(len(filtered_data))
print(filtered_data ['overall'].value_counts())
filtered_data ['sentiment'] = filtered_data ['overall'].apply(get_sentiment)
#train_data = df_short_reviews.sample(n=200000, random_state =0)
train_data = filtered_data[['reviewText','sentiment']]
print('Train data')
print(train_data['sentiment'].value_counts())

#Create Test Data
mask = review_data['Num_words_text'] < 100
df_short_reviews = review_data[mask]
filtered_data = df_short_reviews.groupby('asin').filter(lambda x: len(x) >= 10)
print(len(filtered_data))
print(filtered_data ['overall'].value_counts())
filtered_data ['sentiment'] = filtered_data ['overall'].apply(get_sentiment)
#train_data = df_short_reviews.sample(n=200000, random_state =0)
test_data = filtered_data[['reviewText','sentiment']]
print('Test data')
print(test_data['sentiment'].value_counts())
```

```
47897
5.0    23333
4.0     9707
3.0     4769
2.0     2301
1.0     1706
0.0        1
Name: overall, dtype: int64
Train data
1    37809
0    10088
Name: sentiment, dtype: int64
125888
5.0    62393
4.0    21107
3.0    11732
2.0     5972
1.0     5375
0.0        1
Name: overall, dtype: int64
Test data
1    95232
0    30656
Name: sentiment, dtype: int64
```

3. Architecture Network

Explain the Network Used for this Analysis:

For this analysis, we used a bidirectional RNN with LSTMs to create our encoding layer. A recurrent neural network (RNN) is an artificial neural network that uses sequential or time series input to learn. We are using deep learning algorithms to process natural language (nlp). LSTM networks are a sort of recurrent neural network that can learn order dependence in sequence prediction issues.

3.1 Overview of the Model TensorFlow:

LSTM (Long-Short Term Memory) neural networks are a sort of RNN that is built for long-term dependence and can store information for an extended length of time. When compared to traditional RNN, which may be used to predict future words based on previous work analysis, this method is more efficient.

```
max_features =50000
embedding_dim =16
sequence_length = 100

model = tf.keras.Sequential()
model.add(tf.keras.layers.Embedding(max_features +1, embedding_dim, input_length=sequence_length,\
                                    embeddings_regularizer = regularizers.l2(0.005)))
model.add(tf.keras.layers.Dropout(0.4))

model.add(tf.keras.layers.LSTM(embedding_dim,dropout=0.2, recurrent_dropout=0.2,return_sequences=True,\
                                                          kernel_regularizer=regularizers.l2(0.005),\
                                                          bias_regularizer=regularizers.l2(0.005)))

model.add(tf.keras.layers.Flatten())

model.add(tf.keras.layers.Dense(512, activation='relu',\
                                kernel_regularizer=regularizers.l2(0.001),\
                                bias_regularizer=regularizers.l2(0.001),))
model.add(tf.keras.layers.Dropout(0.4))

model.add(tf.keras.layers.Dense(8, activation='relu',\
                                kernel_regularizer=regularizers.l2(0.001),\
                                bias_regularizer=regularizers.l2(0.001),))
model.add(tf.keras.layers.Dropout(0.4))


model.add(tf.keras.layers.Dense(1,activation='sigmoid'))



model.summary()
model.compile(loss=tf.keras.losses.BinaryCrossentropy(),optimizer=tf.keras.optimizers.Adam(1e-3),metrics=[tf.keras.metrics.Binary
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding (Embedding)        (None, 100, 16)           800016

dropout (Dropout)            (None, 100, 16)           0

lstm (LSTM)                  (None, 100, 16)           2112

flatten (Flatten)            (None, 1600)              0

dense (Dense)                (None, 512)               819712

dropout_1 (Dropout)          (None, 512)               0

dense_1 (Dense)              (None, 8)                 4104

dropout_2 (Dropout)          (None, 8)                 0

dense_2 (Dense)              (None, 1)                 9

=================================================================
Total params: 1,625,953
Trainable params: 1,625,953
Non-trainable params: 0
_________________________________________________________________
```

For this project, an LSTM model was created for sentimental analysis.

- The output shape (100,16) is used to generate an embedding layer. This guarantees that the words are fed into the model according to the sentiment-specific vocabulary generated by word embeddings.
- To avoid the problem of overfitting when data advances further into the layers of the model, two dropout layers are added before and after the LSTM layer.
- The model generates an LSTM bidirectional layer of output shape (128) for the categorization of positive or negative emotion included in the words.
- To capture the output of the LSTM effectively and to stabilize the state of the model throughout 3 epochs, two dense layers of output shape (,64) and (,1) are built.

3.2 Type of Layers:

Layers are the core features of TensorFlow. Here is the list of different available layers

- Core Layer: input_data, fully_connected, dropout, custom_layer, reshape, flatten, activation, single_unit, highway, one_hot_encoding and time_distributed.
- ConvLayer: Conv_2d, Conv_2d_transpose_max_pool_2d, avg_pool_2d, upsample_2d, Conv_1d, max_pool_1d, avg_pool_1d, residual_block, residual_bottleneck, conv_3d, max_pool_3d, avg_pool_3d, highway_conv_1d, highway_conv_2d, global_avg_pool, and global_max_pool.
- Recurrent Layer: Simple_rnn, lstm, gru, bidirectional_rnn and dynamic_rnn
- Embedding Layer: Embedding
- Normalization Layer: Batch_normalization, local_response_normalization and 12_normalize
- Merge Layer: Merge and merge_outputs
- Estimator Layer: regression

In this analysis, we used Recurrent layer with
lstm with (embedding_dim,dropout=0.2, recurrent_dropout=0.2, return_sequences=True) and
Embedding with embedding_dim,dropout=0.2, recurrent_dropout=0.2, return_sequences=True,
Dropout (0,4)
Bidirectional layer with LSTM (64)
Dense layer with (64, activation='relu')

3.3 Neural Networks and affects:

In this sentimental analysis, we used RNN network. A feedforward neural network with an internal memory is known as a recurrent neural network. RNN is recurrent in nature since it performs the same function for each data input, and the current input's outcome is dependent on the previous one's computation. The output is replicated and transmitted back into the recurrent network when it is created. It examines the current input as well as the output from the prior input when deciding. RNNs can model data sequences so that each sample is thought to be reliant on the ones before it. Even convolutional layers and recurrent neural networks are employed to extend the effective pixel neighborhood.

We used LSTM model for this analysis, Long-term memory (LSTM) networks are a modified version of recurrent neural networks that make it easier to recall past material. RNN's vanishing gradient problem is overcome in this paper. Given time lags of uncertain duration, LSTM is well suited to identify, analyses, and predict time series. Using backpropagation, it trains the model. Three gates are included in an LSTM network.

4. Conclusion

According to the above classification report, the model had the simplest time classifying the sentiment of Bad and Excellent reviews but had a more difficult difficulty classifying the sentiment of Fair and Good ratings. The accuracy of Fair and Good predictions was slightly higher than randomly selecting a class.

If we ran this model again, it would be interesting to see if changing the categories affected the model's accuracy. If we combined 4- and 5-star ratings together, we believe the algorithm would be effective in predicting helpful reviews. Also, combining Bad and Fair reviews together as negative would be the same. Another project concept would be to use sentiment analysis to forecast the actual star rating.

References

[1] Title: (Machine Learning A-Z (Availability Zones): Hands-On Python & R in Data Science), SuperDataScience Date: August 15th, 2021, URL: https://www.superdatascience.com/
[2] Title: (Recurrent Neural Network), GeeksForGeeks. URL: https://www.geeksforgeeks.org/introduction-to-recurrent-neural-network/ Date: July 4th, 2019
[3] Title: SuperDataScience, (Machine Learning A-Z: Hands-On Python & R in Data Science) Date: August 15th, 2021, URL: https://www.superdatascience.com/
[4] Title: Sentimental Analysis in Python) Author: Violeta Misheva. URL: https://app.datacamp.com/learn/courses/sentiment-analysis-in-python Date: 2021
[5] Title: (Python code examples of) Author: Y Zhang. URL: https://zhang-yang.medium.com/deep-learning-model-for-product-category-prediction-40600747b22e Date: 2018