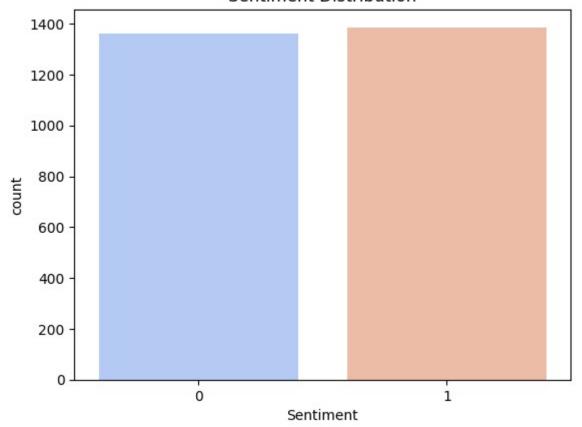
Double-click (or enter) to edit

import warnings

```
warnings.filterwarnings("ignore")
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from nltk.stem import WordNetLemmatizer
from wordcloud import WordCloud, STOPWORDS, ImageColorGenerator
import pandas as pd
import os
import re
import sklearn
from sklearn import preprocessing
from sklearn import model selection
from sklearn.model_selection import train_test split
import tensorflow as tf
from tensorflow.keras.optimizers import Adam
import keras
from keras import preprocessing
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad sequences
from tensorflow.keras.models import Sequential, Model
from tensorflow.keras.layers import LSTM, Dense, Dropout, Input, SpatialDropout1D, Embeddin
from tensorflow.keras.regularizers import 12
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay, classification_report
pd.set_option('display.max_rows', None)
Amazon = pd.read_csv('amazon_cells_labelled.txt', sep='\t', header=None, names=['Review',
IMDB = pd.read_csv('imdb_labelled.txt', sep='\t', header=None, names=['Review', 'Sentiment
Yelp = pd.read_csv('yelp_labelled.txt', sep='\t', header=None, names=['Review', 'Sentiment
df = pd.concat(([Amazon, IMDB, Yelp]))
print(df.shape)
print(df.head())
→ (2748, 2)
                                                    Review Sentiment
       So there is no way for me to plug it in here i...
     0
                                                                    0
     1
                              Good case, Excellent value.
                                                                    1
     2
                                   Great for the jawbone.
                                                                    1
     3
       Tied to charger for conversations lasting more...
                                                                    0
                                        The mic is great.
                                                                    1
```

```
print(df.shape)
print(df.head())
print(" ")
# Visualize the sentiment distribution
df['Sentiment'].value_counts()
sns.countplot(x='Sentiment', data=df, palette='coolwarm')
plt.title('Sentiment Distribution')
plt.show()
print(" ")
print(df['Sentiment'].dtype) # Should be int or float
print(" ")
print(df['Sentiment'].unique())
     (2748, 2)
                                                   Review Sentiment
       So there is no way for me to plug it in here i...
     1
                              Good case, Excellent value.
                                                                    1
     2
                                   Great for the jawbone.
                                                                    1
       Tied to charger for conversations lasting more...
                                                                    0
                                        The mic is great.
                                                                    1
```

Sentiment Distribution



int64

```
[0 1]
df.dropna(inplace=True)
df.isnull().sum()
                0
       Review
                0
      Sentiment 0
     dtype: int64
#Initial list of words/characters in reviews
chars_list = []
for comment in df['Review']:
    for character in comment:
        if character not in chars_list:
            chars_list.append(character)
print(chars_list)
     ['S', 'o', ' ', 't', 'h', 'e', 'r', 'i', 's', 'n', 'w', 'a', 'y', 'f', 'm', 'p', 'l',
import nltk
nltk.download('stopwords')
nltk.download('punkt_tab')
nltk.download('wordnet')
stop words = set(stopwords.words('english'))
lemma = WordNetLemmatizer()
# Process reviews and remove unwanted characters
desc_list = []
for description in df.Review:
    description = re.sub("[^a-zA-Z]", " ", description).lower() # Remove punctuation and
    description = word_tokenize(description) # Tokenize text
    description = [lemma.lemmatize(word) for word in description if word not in stop_word
    desc_list.append(' '.join(description)) # Join back into a single string
print(" ")
tokenizer = Tokenizer()
tokenizer.fit_on_texts(df['Review'])
print("Vocabulary size: ", len(tokenizer.word_index) + 1)
print(" ")
wordcloud = WordCloud(stopwords=stop_words).generate(' '.join(desc_list)) # Join all pro
# Display and save the word cloud
nlt.imshow(wordcloud. internolation='hilinear')
```

```
pre. implion (mol derodd) incel porderon- orirical /
plt.axis("off")
plt.savefig('wordcloud.png')
plt.show()
     [nltk_data] Downloading package stopwords to /root/nltk_data...
                   Unzipping corpora/stopwords.zip.
     [nltk_data]
     [nltk_data] Downloading package punkt_tab to /root/nltk_data...
     [nltk data] Unzipping tokenizers/punkt tab.zip.
     [nltk_data] Downloading package wordnet to /root/nltk_data...
```

Vocabulary size: 5272

review_length = []



```
for char_len in df['Review']:
  review_length.append(len(char_len.split(" ")))
review_max = np.max(review_length)
review_min = np.min(review_length)
review_median = np. median(review_length)
print("Max length is: ", review_max)
print("Median length is ", review median)
print("Min length is: ", review_min)
print(" ")
     Max length is: 1393
     Median length is 11.0
     Min length is: 1
x = np.array(desc_list)
y = df.Sentiment.values
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.20, random_state
v train = nd Series(v train)
```

```
y_c. ain - pa.sc. ics(y_c. ain)
y_test = pd.Series(y_test)
print("Training size: ", x_train.shape)
print("Testing size: ", x_test.shape)
     Training size: (2198,)
     Testing size: (550,)
# Tokenizer setup
tokenizer = Tokenizer()
tokenizer.fit_on_texts(x_train) # Fit tokenizer on training data
word_index = tokenizer.word_index
print(word_index)
print(" ")
print("Vocab Size: ", len(tokenizer.word_index) + 1)
print(f"Number of unique words: {len(tokenizer.word_index)}")
print(" ")
print(f"First 10 words in the word index: {list(tokenizer.word_index.items())[:10]}")
print(" ")
# Calculate the maximum, min, and median review length from the training data
review_length = [len(review.split()) for review in x_train]
review_max = np.max(review_length)
review_min = np.min(review_length)
review_median = np.median(review_length)
# Convert text to sequences (convert words to integers)
seq_train = tokenizer.texts_to_sequences(x_train)
padded_train = pad_sequences(seq_train, maxlen=review_max, padding='post', truncating='po
seq_test = tokenizer.texts_to_sequences(x_test)
padded_test = pad_sequences(seq_test, maxlen=review_max, padding='post', truncating='post
print("Max length is: ", review_max)
print(" ")
print("Median length is ", review_median)
print(" ")
print("Min length is: ", review_min)
print(" ")
print(f"Shape of padded training data: {padded_train.shape}")
print(" ")
print(f"Shape of padded test data: {padded_test.shape}")
print(" ")
print("Padded Training Sequences:")
print(pd.DataFrame(padded_train).head())
print(" ")
print("Padded Test Sequences:")
print(pd.DataFrame(padded_test).head())
```

```
{'good': 1, 'great': 2, 'movie': 3, 'phone': 4, 'film': 5, 'time': 6, 'food': 7, 'pla
Vocab Size: 3938
Number of unique words: 3937
First 10 words in the word index: [('good', 1), ('great', 2), ('movie', 3), ('phone',
Max length is: 677
Median length is 5.0
Min length is: 0
Shape of padded training data: (2198, 677)
Shape of padded test data: (550, 677)
Padded Training Sequences:
                                                7
   0
         1
                       3
                              4
                                   5
                                         6
                                                      8
                                                            9
                                                                       667
                                                                             668
                                                                                   669
0
   176
         275
                  3
                         0
                                0
                                      0
                                           0
                                                  0
                                                        0
                                                              0
                                                                         0
                                                                               0
                                                                                     0
1
    38
         217
              1046
                     1662
                               38
                                    23
                                         741
                                               1663
                                                                         0
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                                                                 . . .
2
   316
         367
                137
                       163
                            1664
                                      0
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3
    18
         317
                  4
                     1665
                            1666
                                   275
                                          50
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    51
         427
                742
                         0
                                                                                     0
   670
         671
              672
                          674
                                675
                                      676
                    673
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1
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2
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3
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                                        0
     0
           0
                 0
4
     0
           0
                 0
                       0
                            0
                                  0
                                        0
[5 rows x 677 columns]
Padded Test Sequences:
                                   5
                                                7
                                                      8
    0
          1
                 2
                       3
                             4
                                         6
                                                            9
                                                                       667
                                                                             668
                                                                                   669
     49
            3
                 105
                        85
                            2217
                                      0
                                           0
                                                        0
                                                                         0
                                                                               0
                                                                                     0
1
   2437
          233
                  14
                       155
                             2761
                                   839
                                         344
                                               1008
                                                                               0
                                                                                     0
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2
   3301
          835
                 168
                       323
                                0
                                      0
                                           0
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                                                              0
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                                                                  . . .
3
     59
           20
                 737
                       252
                                0
                                      0
                                           0
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                                                        0
                                                              0
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                                                                  . . .
4
    107
          498
                1439
                                      0
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                                      676
   670
         671
              672
                    673
                          674
                                675
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                                        0
1
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2
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3
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                       0
                            0
                                  0
                                        0
           0
4
     0
           0
                 0
                            0
[5 rows x 677 columns]
```

training_padded = np.array(padded_train)

training_label = np.array(y_train)

```
test_padded = np.array(padded_test)
test_label = np.array(y_test)
pd.DataFrame(training_padded).to_csv("training_padded.csv")
pd.DataFrame(training_label).to_csv("training_label.csv")
pd.DataFrame(test_padded).to_csv("test_padded.csv")
pd.DataFrame(test_label).to_csv("test_label.csv")
early_stopping_monitor = EarlyStopping(monitor = 'val_loss', patience = 2, restore_best_w
input_dim = len(tokenizer.word_index) + 1
output_dim = 64
adam = Adam(learning rate = 0.0005)
# Build the LSTM Model
model = Sequential()
model.add(Input(shape = (review max,)))
model.add(Embedding(input_dim = len(tokenizer.word_index) + 1, output_dim = output_dim))
model.add(SpatialDropout1D(0.5))
model.add(Bidirectional(LSTM(128, dropout=0.6, recurrent_dropout=0.6)))
model.add(BatchNormalization())
model.add(Dropout(0.5))
model.add(Dense(128, activation='relu', kernel_regularizer=12(0.0001)))
model.add(Dense(64, activation='relu', kernel_regularizer=12(0.0001)))
model.add(Dense(1, activation='sigmoid'))
# Compile the model
model.compile(loss = 'binary_crossentropy', optimizer = 'adam', metrics = ['accuracy'])
# Print the model summary
model.summary()
print(" ")
print(f"Embedding input_dim: {input_dim}")
print(f"Embedding output_dim: {output_dim}")
```

Model: "sequential"

Layer (type)	Output Shape	Param
embedding (Embedding)	(None, 677, 64)	252,03
<pre>spatial_dropout1d (SpatialDropout1D)</pre>	(None, 677, 64)	
bidirectional (Bidirectional)	(None, 256)	197,63
batch_normalization (BatchNormalization)	(None, 256)	1,02
dropout (Dropout)	(None, 256)	
dense (Dense)	(None, 128)	32,89

dense_1 (Dense)	(None, 64)	8,25
dense_2 (Dense)	(None, 1)	ϵ

Total params: 491,905 (1.88 MB)
Trainable params: 491,393 (1.87 MB)
Non-trainable params: 512 (2.00 KB)

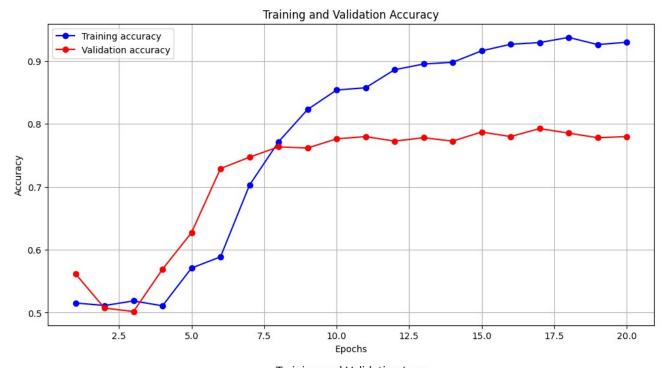
Embedding input_dim: 3938
Embedding output_dim: 64

history = model.fit(padded_train, training_label, epochs = 20, batch_size = 128, validati

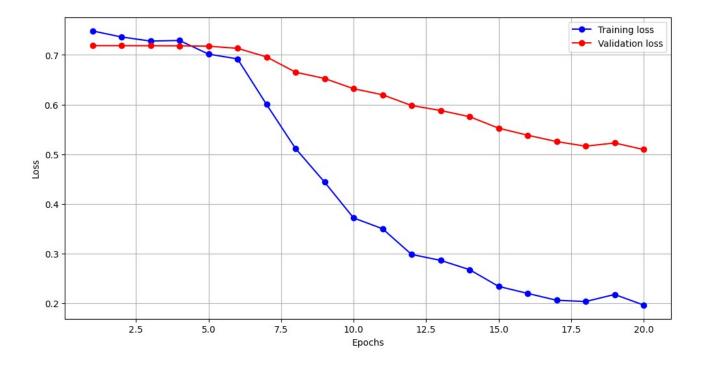
```
Epoch 1/20
                          - 83s 4s/step - accuracy: 0.5013 - loss: 0.7643 - val_accura
18/18 -
Epoch 2/20
18/18 -
                          - 73s 4s/step - accuracy: 0.5223 - loss: 0.7381 - val_accura
Epoch 3/20
                          - 72s 4s/step - accuracy: 0.5217 - loss: 0.7257 - val_accura
18/18 -
Epoch 4/20
                           82s 4s/step - accuracy: 0.4945 - loss: 0.7367 - val_accura
18/18 -
Epoch 5/20
                          - 82s 4s/step - accuracy: 0.5646 - loss: 0.7058 - val_accura
18/18 -
Epoch 6/20
18/18 -
                          - 82s 4s/step - accuracy: 0.5710 - loss: 0.7048 - val_accura
Epoch 7/20
18/18 -
                          - 82s 4s/step - accuracy: 0.6848 - loss: 0.6178 - val_accura
Epoch 8/20
18/18 -
                          - 81s 4s/step - accuracy: 0.7741 - loss: 0.5182 - val_accura
Epoch 9/20
18/18 -
                          - 73s 4s/step - accuracy: 0.8202 - loss: 0.4440 - val_accura
Epoch 10/20
18/18 -
                          - 73s 4s/step - accuracy: 0.8513 - loss: 0.3932 - val_accura
Epoch 11/20
18/18 -
                          - 81s 4s/step - accuracy: 0.8547 - loss: 0.3689 - val_accura
Epoch 12/20
18/18 -
                           82s 4s/step - accuracy: 0.8891 - loss: 0.3017 - val_accura
Epoch 13/20
18/18 -
                           78s 4s/step - accuracy: 0.8913 - loss: 0.2896 - val_accura
Epoch 14/20
18/18 -
                          - 76s 4s/step - accuracy: 0.8959 - loss: 0.2655 - val_accura
Epoch 15/20
18/18 -
                          - 73s 4s/step - accuracy: 0.9150 - loss: 0.2465 - val_accura
Epoch 16/20
                          - 72s 4s/step - accuracy: 0.9271 - loss: 0.2222 - val_accura
18/18 -
Epoch 17/20
18/18 -
                          - 83s 4s/step - accuracy: 0.9252 - loss: 0.2226 - val_accura
Epoch 18/20
18/18 —
                          - 81s 4s/step - accuracy: 0.9442 - loss: 0.1879 - val accura
Epoch 19/20
18/18 -
                          - 81s 4s/step - accuracy: 0.9263 - loss: 0.2179 - val_accura
Epoch 20/20
                          • 79s 4s/step - accuracy: 0.9311 - loss: 0.1879 - val_accura
18/18 -
```

· •

```
# Get the training and validation accuracy and loss
train_accuracy = history.history['accuracy']
val_accuracy = history.history['val_accuracy']
train loss = history.history['loss']
val_loss = history.history['val_loss']
epochs = range(1, len(train_accuracy) + 1) # Epochs range
# Plot training and validation accuracy
plt.figure(figsize=(12, 6))
plt.plot(epochs, train_accuracy, 'bo-', label='Training accuracy')
plt.plot(epochs, val_accuracy, 'ro-', label='Validation accuracy')
plt.title('Training and Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.grid(True)
plt.show()
# Plot training and validation loss
plt.figure(figsize=(12, 6))
plt.plot(epochs, train_loss, 'bo-', label='Training loss')
plt.plot(epochs, val_loss, 'ro-', label='Validation loss')
plt.title('Training and Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.grid(True)
plt.show()
```



Training and Validation Loss



model.save('model.keras')