Source Code and Output-

The IMDB sentiment classification dataset consists of 50,000 movie reviews from IMDB users that are labeled as either positive (1) or negative (0).

The reviews are preprocessed and each one is encoded as a sequence of word indexes in the form of integers.

The words within the reviews are indexed by their overall frequency within the dataset. For example, the integer “2” encodes the second most frequent word in the data.

The 50,000 reviews are split into 25,000 for training and 25,000 for testing.

Text Process word by word at diffrent timestamp (You may use RNN LSTM GRU)

convert input text to vector reprent input text

DOMAIN: Digital content and entertainment industry

CONTEXT: The objective of this project is to build a text classification model that analyses the customer's sentiments based on their reviews in the IMDB database. The model uses a complex deep learning model to build an embedding layer followed by a classification algorithm to analyse the sentiment of the customers.

DATA DESCRIPTION: The Dataset of 50,000 movie reviews from IMDB, labelled by sentiment (positive/negative).

Reviews have been preprocessed, and each review is encoded as a sequence of word indexes (integers).

For convenience, the words are indexed by their frequency in the dataset, meaning the for that has index 1 is the most frequent word.

Use the first 20 words from each review to speed up training, using a max vocabulary size of 10,000.

As a convention, "0" does not stand for a specific word, but instead is used to encode any unknown word.

PROJECT OBJECTIVE: Build a sequential NLP classifier which can use input text parameters to determine the customer sentiments.

```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
#loading imdb data with most frequent 10000 words
from keras.datasets import imdb
(X_train, y_train), (X_test, y_test) = imdb.load_data(num_words=10000) # you may take top 10,000 word frequently used review of movies other are discarded
#consolidating data for EDA Exploratory data analysis (EDA) is used by data scientists to analyze and investigate data sets and summarize their main characteristics
data = np.concatenate((X_train, X_test), axis=0) # axis 0 is first running vertically downwards across rows (axis 0), axis 1 is second running horizontally across columns (axis 1),
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```
label = np.concatenate((y_train, y_test), axis=0)
X_train.shape
(25000,)
X_test.shape
(25000,)
y_train.shape
(25000,)
y_test.shape
(25000,)
print("Review is ",X_train[0]) # series of no converted word to vocabulory associated with index
print("Review is ",y_train[0])
Review is  [1, 194, 1153, 194, 8255, 78, 228, 5, 6, 1463, 4369, 5012, 134, 26, 4, 715, 8, 118, 1634, 14, 394, 20, 13, 119, 954, 189, 102, 5, 207, 110, 3103, 21, 14, 69, 188, 8, 30, 23, 7, 4, 249, 126, 93, 4, 114, 9, 2300, 1523, 5, 647, 4, 116, 9, 35, 8163, 4, 229, 9, 340, 1322, 4, 118, 9, 4, 130, 4901, 19, 4, 1002, 5, 89, 29, 952, 46, 37, 4, 455, 9, 45, 43, 38, 1543, 1905, 398, 4, 1649, 26, 6853, 5, 163, 11, 3215, 2, 4, 1153, 9, 194, 775, 7, 8255, 2, 349, 2637, 148, 605, 2, 8003, 15, 123, 125, 68, 2, 6853, 15, 349, 165, 4362, 98, 5, 4, 228, 9, 43, 2, 1157, 15, 299, 120, 5, 120, 174, 11, 220, 175, 136, 50, 9, 4373, 228, 8255, 5, 2, 656, 245, 2350, 5, 4, 9837, 131, 152, 491, 18, 2, 32, 7464, 1212, 14, 9, 6, 371, 78, 22, 625, 64, 1382, 9, 8, 168, 145, 23, 4, 1690, 15, 16, 4, 1355, 5, 28, 6, 52, 154, 462, 33, 89, 78, 285, 16, 145, 95]
Review is  0
vocab=imdb.get_word_index() # Retrieve the word index file mapping words to indices
print(vocab)
{'fawn': 34701, 'tsukino': 52006, 'nunnery': 52007, 'sonja': 16816, 'vani': 63951, 'woods': 1408, 'spiders': 16115,
y_train
array([1, 0, 0, ..., 0, 1, 0])
y_test
array([0, 1, 1, ..., 0, 0, 0])
# Function to perform relevant sequence adding on the data
# Now it is time to prepare our data. We will vectorize every review and fill it with zeros so that it contains exactly 10000 numbers.
# That means we fill every review that is shorter than 500 with zeros.
# We do this because the biggest review is nearly that long and every input for our neural network needs to have the same size.
# We also transform the targets into floats.
# sequences is name of method the review less than 10000 we perform padding overthere
# binary vectorization code:
```

```
# VECTORIZE as one cannot feed integers into a NN
# Encoding the integer sequences into a binary matrix - one hot encoder basically
# From integers representing words, at various lengths - to a normalized one hot encoded tensor (matrix) of 10k columns
def vectorize(sequences, dimension = 10000):    # We will vectorize every review and fill it with zeros so that it contains exactly 10,000 numbers.
  # Create an all-zero matrix of shape (len(sequences), dimension)
    results = np.zeros((len(sequences), dimension))
    for i, sequence in enumerate(sequences):
        results[i, sequence] = 1
    return results
# Now we split our data into a training and a testing set.
# The training set will contain  reviews and the testing set
# # Set a VALIDATION set

test_x  =  data[:10000]
test_y  =  label[:10000]
train_x  =  data[10000:]
train_y = label[10000:]
test_x.shape
(10000,)
test_y.shape
(10000,)
train_x.shape
(40000,)
train_y.shape
(40000,)
print("Categories:", np.unique(label))
print("Number of unique words:", len(np.unique(np.hstack(data))))
# The hstack() function is used to stack arrays in sequence horizontally (column wise).
Categories: [0 1]
Number of unique words: 9998
length = [len(i) for i in data]
print("Average Review length:", np.mean(length))
print("Standard Deviation:", round(np.std(length)))

# The whole dataset contains 9998 unique words and the average review length is 234 words, with a standard deviation of 173 words.
```

```
Average Review length: 234.75892
Standard Deviation: 173
# If you look at the data you will realize it has been already pre-processed.
# All words have been mapped to integers and the integers represent the words sorted by their frequency.
# This is very common in text analysis to represent a dataset like this.
# So 4 represents the 4th most used word,
# 5 the 5th most used word and so on...
# The integer 1 is reserved for the start marker,
# the integer 2 for an unknown word and 0 for padding.

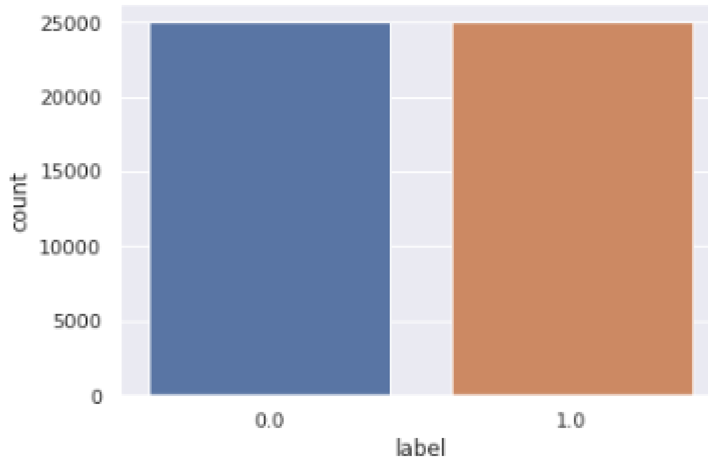
# Let's look at a single training example:

print("Label:", label[0])
Label: 1
print("Label:", label[1])
Label: 0
print(data[0])
# Retrieves a dict mapping words to their index in the IMDB dataset.
index = imdb.get_word_index() # word to index
# Create inverted index from a dictionary with document ids as keys and a list of terms as values for each document
reverse_index = dict([(value, key) for (key, value) in index.items()]) # id to word

decoded = " ".join( [reverse_index.get(i - 3, "#") for i in data[0]] )
# The indices are offset by 3 because 0, 1 and 2 are reserved indices for "padding", "start of sequence" and "unknown".
print(decoded)
# this film was just brilliant casting location scenery story direction everyone's really suited the part they played and you could just imagine being there robert # is an amazing actor and now the same being director # father came from the same scottish island as myself so i loved the fact there was a real connection with this film the witty remarks throughout the film
#Adding sequence to data
# Vectorization is the process of converting textual data into numerical vectors and is a process that is usually applied once the text is cleaned.
data = vectorize(data)
```

```
label = np.array(label).astype("float32")
labelDF=pd.DataFrame({'label':label})
sns.countplot(x='label', data=labelDF)
```

```
<AxesSubplot:xlabel='label', ylabel='count'>
```




```
# Creating train and test data set
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(data,label, test_size=0.20, random_state=1)
X_train.shape
(40000, 10000)
X_test.shape
(10000, 10000)
# Let's create sequential model
from keras.utils import to_categorical
from keras import models
from keras import layers
model = models.Sequential()
# Input - Layer
# Note that we set the input-shape to 10,000 at the input-layer because our reviews are 10,000 integers long.
# The input-layer takes 10,000 as input and outputs it with a shape of 50.
model.add(layers.Dense(50, activation = "relu", input_shape=(10000, )))
# Hidden - Layers
# Please note you should always use a dropout rate between 20% and 50%. # here in our case 0.3 means 30% dropout we are using dropout to prevent overfitting.
# By the way, if you want you can build a sentiment analysis without LSTMs, then you simply need to replace it by a flatten layer:
model.add(layers.Dropout(0.3, noise_shape=None, seed=None))
```

```
model.add(layers.Dense(50, activation = "relu"))
model.add(layers.Dropout(0.2, noise_shape=None, seed=None))
model.add(layers.Dense(50, activation = "relu"))
# Output- Layer
model.add(layers.Dense(1, activation = "sigmoid"))
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 50)                500050

 dropout (Dropout)           (None, 50)                0

 dense_1 (Dense)             (None, 50)                2550

 dropout_1 (Dropout)         (None, 50)                0

 dense_2 (Dense)             (None, 50)                2550

 dense_3 (Dense)             (None, 1)                 51

=================================================================
Total params: 505,201
Trainable params: 505,201
Non-trainable params: 0
```

```
#For early stopping
# Stop training when a monitored metric has stopped improving.
# monitor: Quantity to be monitored.
# patience: Number of epochs with no improvement after which training will be stopped.
import tensorflow as tf
callback = tf.keras.callbacks.EarlyStopping(monitor='loss', patience=3)
# We use the “adam” optimizer, an algorithm that changes the weights and biases during training.
# We also choose binary-crossentropy as loss (because we deal with binary classification) and accuracy as our evaluation metric.

model.compile(
 optimizer = "adam",
 loss = "binary_crossentropy",
 metrics = ["accuracy"]
)
```

```
from sklearn.model_selection import train_test_split

results = model.fit(
 X_train, y_train,
 epochs= 2,
 batch_size = 500,
 validation_data = (X_test, y_test),
 callbacks=[callback]
)
# Let's check mean accuracy of our model
print(np.mean(results.history["val_accuracy"]))
# Evaluate the model
score = model.evaluate(X_test, y_test, batch_size=500)
print('Test loss:', score[0])
print('Test accuracy:', score[1])
20/20 [==============================] - 1s 24ms/step - loss: 0.2511 - accuracy:
0.8986
Test loss: 0.25108325481414795
Test accuracy: 0.8985999822616577
#Let's plot training history of our model.

# list all data in history
print(results.history.keys())
# summarize history for accuracy
plt.plot(results.history['accuracy'])
plt.plot(results.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()
# summarize history for loss
plt.plot(results.history['loss'])
plt.plot(results.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
```

```
plt.legend(['train', 'test'], loc='upper left')
plt.show()
```

```
dict_keys(['loss', 'accuracy', 'val_loss', 'val_accuracy'])
```