# Group B Deep Learning

## Assignment No: 2A

**Source Code and Output-**

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# 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
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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),
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
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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))))
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# 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
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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

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#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)
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<AxesSubplot:xlabel='label', ylabel='count'>
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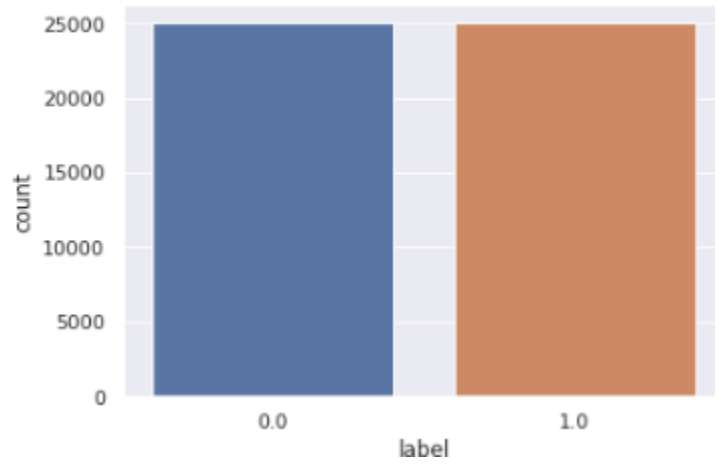


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# Creating train and test data set
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(data,label, test_size=0.20, random_state=1)
X_train.shape
(40000, 10000)
X_test.shape
(10000, 10000)
# Let's 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, )))
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# 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()
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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
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#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
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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')
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plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()
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dict_keys(['loss', 'accuracy', 'val_loss', 'val_accuracy'])
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