sentiment_analysis_using_lstm_pytorch

May 6, 2022

In this kernel we will go through a sentiment analysis on imdb dataset using LSTM.

[1]:
```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import torch
import torch.optim
import torch.nn as nn
from   torch.nn import Parameter
from   torch import autograd
import torch.nn.functional as F
from   torch.autograd import Variable
from nltk.corpus import stopwords
from collections import Counter
import string
import re
import seaborn as sns
from tqdm import tqdm
import matplotlib.pyplot as plt
from torch.utils.data import TensorDataset, DataLoader
from sklearn.model_selection import train_test_split
```

[2]:
```
is_cuda = torch.cuda.is_available()

# If we have a GPU available, we'll set our device to GPU. We'll use this␣
 ↪device variable later in our code.
if is_cuda:
    device = torch.device("cuda")
    print("GPU is available")
else:
    device = torch.device("cpu")
    print("GPU not available, CPU used")
```

```
GPU is available
```

[3]:
```
from google.colab import drive
drive.mount('/content/drive')
%cd /content/drive/MyDrive/asr/sentiment2/
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
```

```
drive.mount("/content/drive", force_remount=True).
/content/drive/MyDrive/asr/sentiment2
```

[4]:
```
!ls
```

```
 core_qnn            __pycache__           small.csv
'IMDB Dataset.csv'   recurrent_models.py   state_dict.pt
```

[5]:
```
base_csv = 'small.csv'
df = pd.read_csv(base_csv)
df.head()
```

[5]:

	review	sentiment
0	One of the other reviewers has mentioned that …	positive
1	A wonderful little production. The…	positive
2	I thought this was a wonderful way to spend ti…	positive
3	Basically there's a family where a little boy …	negative
4	Petter Mattei's "Love in the Time of Money" is…	positive

0.0.1 Splitting to train and test data

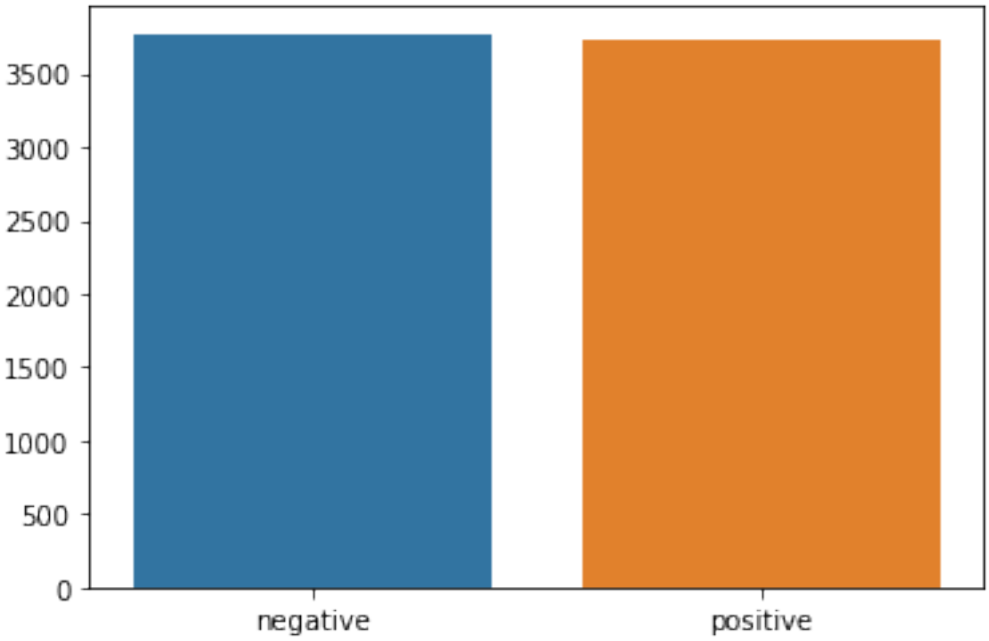
We will split data to train and test initially.Doing this on earlier stage allows to avoid data lekage.

[6]:
```
X,y = df['review'].values,df['sentiment'].values
x_train,x_test,y_train,y_test = train_test_split(X,y,stratify=y)
print(f'shape of train data is {x_train.shape}')
print(f'shape of test data is {x_test.shape}')
```

```
shape of train data is (7500,)
shape of test data is (2500,)
```

0.0.2 Analysing sentiment

[7]:
```
dd = pd.Series(y_train).value_counts()
sns.barplot(x=np.array(['negative','positive']),y=dd.values)
plt.show()
```



0.0.3 Tockenization

[8]:
```
def preprocess_string(s):
    # Remove all non-word characters (everything except numbers and letters)
    s = re.sub(r"[^\w\s]", '', s)
    # Replace all runs of whitespaces with no space
    s = re.sub(r"\s+", '', s)
    # replace digits with no space
    s = re.sub(r"\d", '', s)

    return s

def tockenize(x_train,y_train,x_val,y_val):
    word_list = []

    stop_words = set(stopwords.words('english'))
    for sent in x_train:
        for word in sent.lower().split():
            word = preprocess_string(word)
            if word not in stop_words and word != '':
                word_list.append(word)

    corpus = Counter(word_list)
    # sorting on the basis of most common words
    corpus_ = sorted(corpus,key=corpus.get,reverse=True)[:1000]
```

```
    # creating a dict
    onehot_dict = {w:i+1 for i,w in enumerate(corpus_)}

    # tockenize
    final_list_train,final_list_test = [],[]
    for sent in x_train:
            final_list_train.append([onehot_dict[preprocess_string(word)] for␣
↪word in sent.lower().split()
                                     if preprocess_string(word) in onehot_dict.
↪keys()])
    for sent in x_val:
            final_list_test.append([onehot_dict[preprocess_string(word)] for␣
↪word in sent.lower().split()
                                    if preprocess_string(word) in onehot_dict.
↪keys()])

    encoded_train = [1 if label =='positive' else 0 for label in y_train]
    encoded_test = [1 if label =='positive' else 0 for label in y_val]
    return np.array(final_list_train), np.array(encoded_train),np.
↪array(final_list_test), np.array(encoded_test),onehot_dict
```

[9]:
```
!pip3 install nltk
import nltk
nltk.download('stopwords')
```

```
Requirement already satisfied: nltk in /usr/local/lib/python3.7/dist-packages
(3.2.5)
Requirement already satisfied: six in /usr/local/lib/python3.7/dist-packages
(from nltk) (1.15.0)
[nltk_data] Downloading package stopwords to /root/nltk_data…
[nltk_data]   Package stopwords is already up-to-date!
```

[9]:
```
True
```

[10]:
```
x_train,y_train,x_test,y_test,vocab = tockenize(x_train,y_train,x_test,y_test)
```

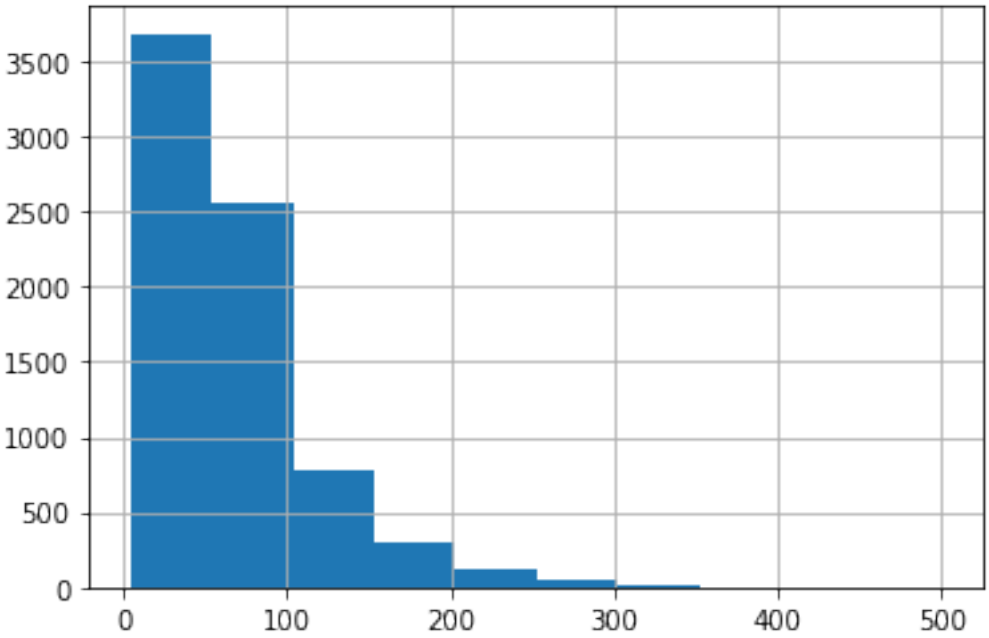
```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:38:
VisibleDeprecationWarning: Creating an ndarray from ragged nested sequences
(which is a list-or-tuple of lists-or-tuples-or ndarrays with different lengths
or shapes) is deprecated. If you meant to do this, you must specify
'dtype=object' when creating the ndarray.
```

[11]:
```
print(f'Length of vocabulary is {len(vocab)}')
```

```
Length of vocabulary is 1000
```

0.0.4 Analysing review length

[12]:
```
rev_len = [len(i) for i in x_train]
pd.Series(rev_len).hist()
plt.show()
pd.Series(rev_len).describe()
```



[12]:
```
count    7500.000000
mean       69.095200
std        48.229861
min         4.000000
25%        39.000000
50%        54.000000
75%        84.000000
max       501.000000
dtype: float64
```

Observations : a) Mean review length = around 69. b) minimum length of reviews is 2.c)There are quite a few reviews that are extremely long, we can manually investigate them to check whether we need to include or exclude them from our analysis.

0.0.5 Padding

Now we will pad each of the sequence to max length

[13]:
```
def padding_(sentences, seq_len):
    features = np.zeros((len(sentences), seq_len),dtype=int)
```

```
    for ii, review in enumerate(sentences):
        if len(review) != 0:
            features[ii, -len(review):] = np.array(review)[:seq_len]
    return features
```

[14]:
```
#we have very less number of reviews with length > 500.
#So we will consideronly those below it.
x_train_pad = padding_(x_train,500)
x_test_pad = padding_(x_test,500)
```

0.0.6 Batching and loading as tensor

[15]:
```
# create Tensor datasets
train_data = TensorDataset(torch.from_numpy(x_train_pad), torch.
 ↪from_numpy(y_train))
valid_data = TensorDataset(torch.from_numpy(x_test_pad), torch.
 ↪from_numpy(y_test))

# dataloaders
batch_size = 50

# make sure to SHUFFLE your data
train_loader = DataLoader(train_data, shuffle=True, batch_size=batch_size)
valid_loader = DataLoader(valid_data, shuffle=True, batch_size=batch_size)
```

[16]:
```
# obtain one batch of training data
dataiter = iter(train_loader)
sample_x, sample_y = dataiter.next()

print('Sample input size: ', sample_x.size()) # batch_size, seq_length
print('Sample input: \n', sample_x)
print('Sample output: \n', sample_y)
```

```
Sample input size:  torch.Size([50, 500])
Sample input:
 tensor([[  0,   0,   0,  …,  13, 191, 330],
        [  0,   0,   0,  …, 186, 852, 199],
        [  0,   0,   0,  …, 389, 660, 258],
        …,
        [  0,   0,   0,  …, 168, 102,   4],
        [  0,   0,   0,  …, 857,   8, 164],
        [  0,   0,   0,  …,  54,   9, 476]])
Sample output:
 tensor([1, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 0,
        1, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 1, 1, 0, 1, 0, 0, 1, 1, 1, 1, 0, 1,
        0, 1])
```

We need to add an embedding layer because there are less words in our vocabulary. It is massively

inefficient to one-hot encode that many classes. So, instead of one-hot encoding, we can have an embedding layer and use that layer as a lookup table. You could train an embedding layer using Word2Vec, then load it here. But, it's fine to just make a new layer, using it for only dimensionality reduction, and let the network learn the weights.

0.0.7 Model

[17]:
```
import math
from core_qnn.quaternion_layers import *

class LSTM(nn.Module):
    def __init__(self, input_sz: int, hidden_sz: int):
        super().__init__()
        self.input_size = input_sz
        self.hidden_size = hidden_sz

        #i_t
        self.W_i = nn.Linear(input_sz, hidden_sz)
        self.U_i = nn.Linear(hidden_sz, hidden_sz, bias=False)

        #f_t
        self.W_f = nn.Linear(input_sz, hidden_sz)
        self.U_f = nn.Linear(hidden_sz, hidden_sz, bias=False)

        #c_t
        self.W_c = nn.Linear(input_sz, hidden_sz)
        self.U_c = nn.Linear(hidden_sz, hidden_sz, bias=False)

        #o_t
        self.W_o = nn.Linear(input_sz, hidden_sz)
        self.U_o = nn.Linear(hidden_sz, hidden_sz, bias=False)

        self.init_weights()

    def init_weights(self):
        stdv = 1.0 / math.sqrt(self.hidden_size)
        for weight in self.parameters():
            weight.data.uniform_(-stdv, stdv)

    def forward(self,
                x,
                init_states=None):

        """
        assumes x.shape represents (batch_size, sequence_size, input_size)
        """
        bs, seq_sz, _ = x.size()
```

```
        hidden_seq = []

        if init_states is None:
            h_t, c_t = (
                torch.zeros(bs, self.hidden_size),
                torch.zeros(bs, self.hidden_size),
            )
        else:
            h_t, c_t = init_states

        for t in range(seq_sz):
            x_t = x[:, t, :]
            i_t = torch.sigmoid(self.W_i(x_t) + self.U_i(h_t))
            f_t = torch.sigmoid(self.W_f(x_t) + self.U_f(h_t))
            g_t = torch.tanh(self.W_c(x_t) + self.U_c(h_t))
            o_t = torch.sigmoid(self.W_o(x_t) + self.U_o(h_t))
            c_t = f_t * c_t + i_t * g_t
            h_t = o_t * torch.tanh(c_t)

            hidden_seq.append(h_t.unsqueeze(0))

        #reshape hidden_seq p/ retornar
        hidden_seq = torch.cat(hidden_seq, dim=0)
        hidden_seq = hidden_seq.transpose(0, 1).contiguous()
        return hidden_seq, (h_t, c_t)
```

[18]:
```
class SentimentRNN(nn.Module):
    def __init__(self,no_layers,vocab_size,hidden_dim,embedding_dim,drop_prob=0.
↪5):
        super(SentimentRNN,self).__init__()

        self.output_dim = output_dim
        self.hidden_dim = hidden_dim

        self.no_layers = no_layers
        self.vocab_size = vocab_size

        # embedding and LSTM layers
        self.embedding = nn.Embedding(vocab_size, embedding_dim)

        #lstm
        # self.lstm = nn.LSTM(input_size=embedding_dim,hidden_size=self.
↪hidden_dim,
        #                     num_layers=no_layers, batch_first=True)
        self.lstm = LSTM(embedding_dim, self.hidden_dim)
```

```
        # dropout layer
        self.dropout = nn.Dropout(0.3)

        # linear and sigmoid layer
        self.fc = nn.Linear(self.hidden_dim, output_dim)
        self.sig = nn.Sigmoid()

    def forward(self,x,hidden):
        batch_size = x.size(0)
        # embeddings and lstm_out
        embeds = self.embedding(x)  # shape: B x S x Feature   since batch =
↪True
        #print(embeds.shape)  #[50, 500, 1000]
        lstm_out, hidden = self.lstm(embeds, hidden)

        lstm_out = lstm_out.contiguous().view(-1, self.hidden_dim)

        # dropout and fully connected layer
        out = self.dropout(lstm_out)
        out = self.fc(out)

        # sigmoid function
        sig_out = self.sig(out)

        # reshape to be batch_size first
        sig_out = sig_out.view(batch_size, -1)

        sig_out = sig_out[:, -1] # get last batch of labels

        # return last sigmoid output and hidden state
        return sig_out, hidden



    def init_hidden(self, batch_size):
        ''' Initializes hidden state '''
        # Create two new tensors with sizes n_layers x batch_size x hidden_dim,
        # initialized to zero, for hidden state and cell state of LSTM
        h0 = torch.zeros((self.no_layers,batch_size,self.hidden_dim)).to(device)
        c0 = torch.zeros((self.no_layers,batch_size,self.hidden_dim)).to(device)
        hidden = (h0,c0)
        return hidden
```

[19]:
```
no_layers = 2
vocab_size = len(vocab) + 1 #extra 1 for padding
```

```
embedding_dim = 64
output_dim = 1
hidden_dim = 256


model = SentimentRNN(no_layers,vocab_size,hidden_dim,embedding_dim,drop_prob=0.
↪5)

#moving to gpu
model.to(device)

print(model)
```

```
SentimentRNN(
  (embedding): Embedding(1001, 64)
  (lstm): LSTM(
    (W_i): Linear(in_features=64, out_features=256, bias=True)
    (U_i): Linear(in_features=256, out_features=256, bias=False)
    (W_f): Linear(in_features=64, out_features=256, bias=True)
    (U_f): Linear(in_features=256, out_features=256, bias=False)
    (W_c): Linear(in_features=64, out_features=256, bias=True)
    (U_c): Linear(in_features=256, out_features=256, bias=False)
    (W_o): Linear(in_features=64, out_features=256, bias=True)
    (U_o): Linear(in_features=256, out_features=256, bias=False)
  )
  (dropout): Dropout(p=0.3, inplace=False)
  (fc): Linear(in_features=256, out_features=1, bias=True)
  (sig): Sigmoid()
)
```

0.0.8 Training

[20]:
```
# loss and optimization functions
lr=0.001

criterion = nn.BCELoss()

optimizer = torch.optim.Adam(model.parameters(), lr=lr)

# function to predict accuracy
def acc(pred,label):
    pred = torch.round(pred.squeeze())
    return torch.sum(pred == label.squeeze()).item()
```

[21]:
```
clip = 5
epochs = 5
valid_loss_min = np.Inf
```

```
# train for some number of epochs
epoch_tr_loss,epoch_vl_loss = [],[]
epoch_tr_acc,epoch_vl_acc = [],[]

import time

start_time = time.time()

for epoch in range(epochs):
    train_losses = []
    train_acc = 0.0
    model.train()
    # initialize hidden state
    h = model.init_hidden(batch_size)
    for inputs, labels in train_loader:

        inputs, labels = inputs.to(device), labels.to(device)
        # Creating new variables for the hidden state, otherwise
        # we'd backprop through the entire training history
        h = tuple([each.data for each in h])

        model.zero_grad()
        output,_ = model(inputs,h)

        # calculate the loss and perform backprop
        loss = criterion(output.squeeze(), labels.float())
        loss.backward()
        train_losses.append(loss.item())
        # calculating accuracy
        accuracy = acc(output,labels)
        train_acc += accuracy
        #`clip_grad_norm` helps prevent the exploding gradient problem in RNNs /
↪ LSTMs.
        nn.utils.clip_grad_norm_(model.parameters(), clip)
        optimizer.step()



    val_h = model.init_hidden(batch_size)
    val_losses = []
    val_acc = 0.0
    model.eval()
    for inputs, labels in valid_loader:
            val_h = tuple([each.data for each in val_h])

            inputs, labels = inputs.to(device), labels.to(device)
```

```
            output, val_h = model(inputs, val_h)
            val_loss = criterion(output.squeeze(), labels.float())

            val_losses.append(val_loss.item())

            accuracy = acc(output,labels)
            val_acc += accuracy

    epoch_train_loss = np.mean(train_losses)
    epoch_val_loss = np.mean(val_losses)
    epoch_train_acc = train_acc/len(train_loader.dataset)
    epoch_val_acc = val_acc/len(valid_loader.dataset)
    epoch_tr_loss.append(epoch_train_loss)
    epoch_vl_loss.append(epoch_val_loss)
    epoch_tr_acc.append(epoch_train_acc)
    epoch_vl_acc.append(epoch_val_acc)
    print(f'Epoch {epoch+1}')
    print(f'train_loss : {epoch_train_loss} val_loss : {epoch_val_loss}')
    print(f'train_accuracy : {epoch_train_acc*100} val_accuracy :␣
↪{epoch_val_acc*100}')
    if epoch_val_loss <= valid_loss_min:
        torch.save(model.state_dict(), 'state_dict.pt')
        print('Validation loss decreased ({:.6f} --> {:.6f}).  Saving model ...
↪'.format(valid_loss_min,epoch_val_loss))
        valid_loss_min = epoch_val_loss
    print(25*'==')

time_taken = time.time() - start_time
print(f'Time taken: {time_taken} s')
```

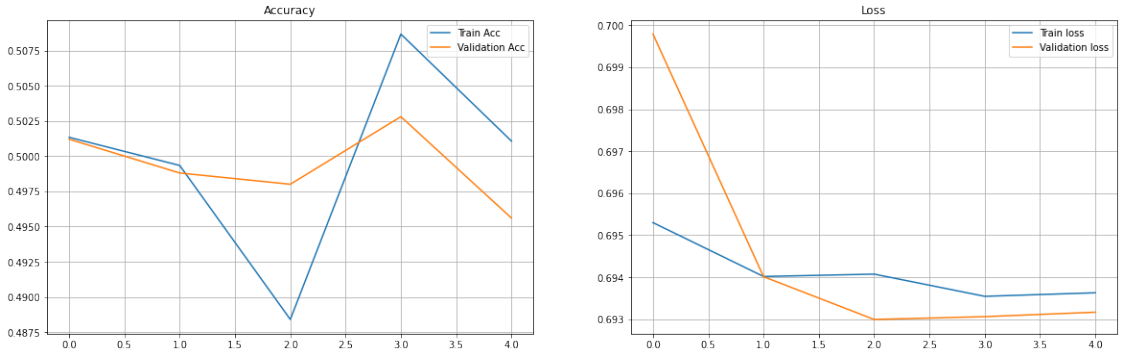
```
Epoch 1
train_loss : 0.6953002727031707 val_loss : 0.6997883737087249
train_accuracy : 50.13333333333333 val_accuracy : 50.12
Validation loss decreased (inf --> 0.699788).  Saving model …
==================================================
Epoch 2
train_loss : 0.6940183524290721 val_loss : 0.6940132117271424
train_accuracy : 49.93333333333334 val_accuracy : 49.88
Validation loss decreased (0.699788 --> 0.694013).  Saving model …
==================================================
Epoch 3
train_loss : 0.6940748528639475 val_loss : 0.692995845079422
train_accuracy : 48.84 val_accuracy : 49.8
Validation loss decreased (0.694013 --> 0.692996).  Saving model …
==================================================
Epoch 4
train_loss : 0.6935462562243143 val_loss : 0.6930617749691009
```

```
train_accuracy : 50.866666666666674 val_accuracy : 50.28
==================================================
Epoch 5
train_loss : 0.6936303385098775 val_loss : 0.6931677722930908
train_accuracy : 50.10666666666667 val_accuracy : 49.559999999999995
==================================================
Time taken: 934.5813076496124 s
```

[22]:
```
fig = plt.figure(figsize = (20, 6))
plt.subplot(1, 2, 1)
plt.plot(epoch_tr_acc, label='Train Acc')
plt.plot(epoch_vl_acc, label='Validation Acc')
plt.title("Accuracy")
plt.legend()
plt.grid()

plt.subplot(1, 2, 2)
plt.plot(epoch_tr_loss, label='Train loss')
plt.plot(epoch_vl_loss, label='Validation loss')
plt.title("Loss")
plt.legend()
plt.grid()

plt.show()
```



0.0.9 Inferance

[23]:
```
def predict_text(text):
        word_seq = np.array([vocab[preprocess_string(word)] for word in text.
 ↪split()
                         if preprocess_string(word) in vocab.keys()])
        word_seq = np.expand_dims(word_seq,axis=0)
        pad =  torch.from_numpy(padding_(word_seq,500))
        inputs = pad.to(device)
```

```
        batch_size = 1
        h = model.init_hidden(batch_size)
        h = tuple([each.data for each in h])
        output, h = model(inputs, h)
        return(output.item())
```

[24]:
```
index = 30
print(df['review'][index])
print('='*70)
print(f'Actual sentiment is  : {df["sentiment"][index]}')
print('='*70)
pro = predict_text(df['review'][index])
status = "positive" if pro > 0.5 else "negative"
pro = (1 - pro) if status == "negative" else pro
print(f'Predicted sentiment is {status} with a probability of {pro}')
```

```
Taut and organically gripping, Edward Dmytryk's Crossfire is a distinctive
suspense thriller, an unlikely "message" movie using the look and devices of the
noir cycle.<br /><br />Bivouacked in Washington, DC, a company of soldiers cope
with their restlessness by hanging out in bars. Three of them end up at a
stranger's apartment where Robert Ryan, drunk and belligerent, beats their host
(Sam Levene) to death because he happens to be Jewish. Police detective Robert
Young investigates with the help of Robert Mitchum, who's assigned to Ryan's
outfit. Suspicion falls on the second of the three (George Cooper), who has
vanished. Ryan slays the third buddy (Steve Brodie) to insure his silence before
Young closes in.<br /><br />Abetted by a superior script by John Paxton, Dmytryk
draws precise performances from his three starring Bobs. Ryan, naturally, does
his prototypical Angry White Male (and to the hilt), while Mitchum underplays
with his characteristic alert nonchalance (his role, however, is not central);
Young may never have been better. Gloria Grahame gives her first fully-fledged
rendition of the smart-mouthed, vulnerable tramp, and, as a sad sack who's
leeched into her life, Paul Kelly haunts us in a small, peripheral role that he
makes memorable.<br /><br />The politically engaged Dmytryk perhaps inevitably
succumbs to sermonizing, but it's pretty much confined to Young's reminiscence
of how his Irish grandfather died at the hands of bigots a century earlier
(thus, incidentally, stretching chronology to the limit). At least there's no
attempt to render an explanation, however glib, of why Ryan hates Jews (and
hillbillies and…).<br /><br />Curiously, Crossfire survives even the major
change wrought upon it -- the novel it's based on (Richard Brooks' The Brick
Foxhole) dealt with a gay-bashing murder. But homosexuality in 1947 was still
Beyond The Pale. News of the Holocaust had, however, begun to emerge from the
ashes of Europe, so Hollywood felt emboldened to register its protest against
anti-Semitism (the studios always quaked at the prospect of offending any
potential ticket buyer).<br /><br />But while the change from homophobia to
anti-Semitism works in general, the specifics don't fit so smoothly. The
victim's chatting up a lonesome, drunk young soldier then inviting him back home
looks odd, even though (or especially since) there's a girlfriend in tow. It
raises the question whether this scenario was retained inadvertently or left in
```

```
as a discreet tip-off to the original engine generating Ryan's murderous rage.
======================================================================
Actual sentiment is  : positive
======================================================================
Predicted sentiment is negative with a probability of 0.5338696837425232
```

[25]:
```
index = 32
print(df['review'][index])
print('='*70)
print(f'Actual sentiment is  : {df["sentiment"][index]}')
print('='*70)
pro = predict_text(df['review'][index])
status = "positive" if pro > 0.5 else "negative"
pro = (1 - pro) if status == "negative" else pro
print(f'predicted sentiment is {status} with a probability of {pro}')
```

```
My first exposure to the Templarios & not a good one. I was excited to find this
title among the offerings from Anchor Bay Video, which has brought us other cult
classics such as "Spider Baby". The print quality is excellent, but this alone
can't hide the fact that the film is deadly dull. There's a thrilling opening
sequence in which the villagers exact a terrible revenge on the Templars (& set
the whole thing in motion), but everything else in the movie is slow, ponderous
&, ultimately, unfulfilling. Adding insult to injury: the movie was dubbed, not
subtitled, as promised on the video jacket.
======================================================================
Actual sentiment is  : negative
======================================================================
predicted sentiment is negative with a probability of 0.517459362745285
```

Some improvement suggestions are as follow:

- Running a hyperparameter search to optimize your configurations.
- Using pretraned word embeddings like Glove word embeddings
- Increasing the model complexity like adding more layers/ using bidirectional LSTMs

[25]: