

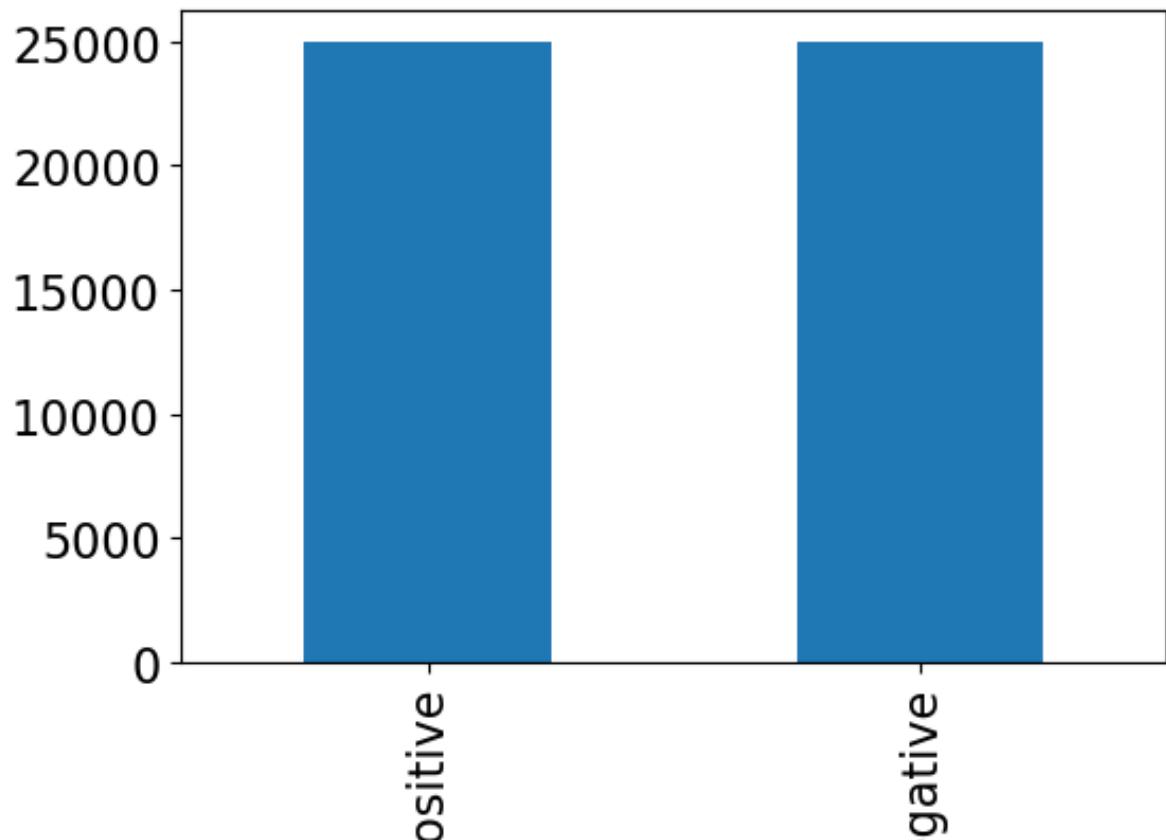
```
In [2]: import os
import numpy as np
import pandas as pd
import random
import matplotlib.pyplot as plt
plt.rcParams.update({'font.size':16})

data = pd.read_csv('IMDB Dataset.csv')

# display the first 5 rows of data
print()
print(data.head(5))

print('\n')
plt.figure(figsize = (6,4))
data['sentiment'].value_counts().plot(kind = 'bar')
plt.show()
```

	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



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```
In [8]: # Choose randomly a positive review and a negative review
ind_positive = random.choice(list(data[data['sentiment'] == 'positive']))
ind_negative = random.choice(list(data[data['sentiment'] == 'negative']))

review_positive = data['review'][ind_positive]
review_negative = data['review'][ind_negative]

print('Positive review: ', review_positive)
print('\n')
print('Negative review: ', review_negative)
print('\n')

from wordcloud import WordCloud
cloud_positive = WordCloud().generate(review_positive)
cloud_negative = WordCloud().generate(review_negative)

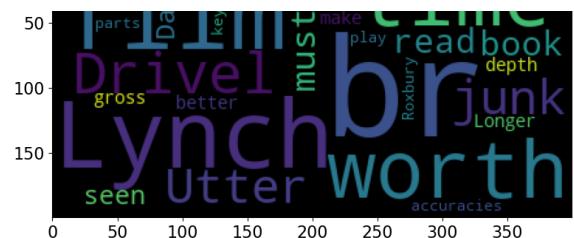
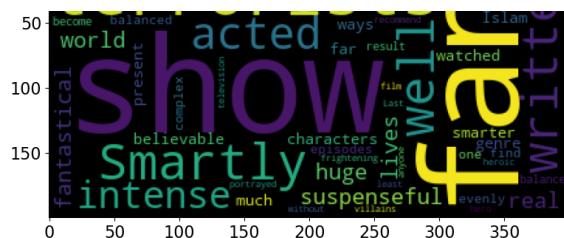
plt.figure(figsize = (20,15))
plt.subplot(1,2,1)
plt.imshow(cloud_positive)
plt.title('Positive review')

plt.subplot(1,2,2)
plt.imshow(cloud_negative)
plt.title('Negative review')
plt.show()
```

Positive review: Smartly written, well acted, intense and suspenseful. This show lives in the real world, not as fantastical as is "24", (and I am a huge fan of 24, incidentally). It has believable characters and in many ways is much smarter than most in this genre. It tries to present both sides of Islam. So far, I have watched the first 4 episodes and find the story to be more evenly balanced. The terrorists are more complex and not one dimensional. And as a result of that balance, the terrorists become more frightening than the typical villains being portrayed in film and on television. Last but not least, the hero is truly heroic without being a cartoon. I recommend this show for anyone who is a fan of 24 and the like.

Negative review: Drivel. Utter junk. The writers must not have read the book, or seen David Lynch's film. Not worth wasting your time.
Longer does not make better. While more in-depth than Lynch's film, it has gross inaccuracies, and down-play's key parts of the story.
"A Night at the Roxbury" is more worth your time.





In [9]: `import re`

```
def remove_url(text):
    url_tag = re.compile(r'https://\S+|www\.\S+')
    text = url_tag.sub(r'', text)
    return text

def remove_html(text):
    html_tag = re.compile(r'<.*?>')
    text = html_tag.sub(r'', text)
    return text

def remove_punctuation(text):
    punct_tag = re.compile(r'[^\w\s]')
    text = punct_tag.sub(r'', text)
    return text

def remove_special_character(text):
    special_tag = re.compile(r'[^a-zA-Z0-9\s]')
    text = special_tag.sub(r'', text)
    return text

def remove_emojis(text):
    emoji_pattern = re.compile("["
        u"\U0001F600-\U0001F64F" # emoticons
        u"\U0001F300-\U0001F5FF" # symbols
        u"\U0001F680-\U0001F6FF" # transport
        u"\U0001F1E0-\U0001F1FF" # flags (including country codes)
    "]+", flags=re.UNICODE)
    text = emoji_pattern.sub(r'', text)
    return text

def clean_text(text):
    text = remove_url(text)
    text = remove_html(text)
    text = remove_punctuation(text)
    text = remove_special_character(text)
    text = remove_emojis(text)
    text = text.lower()

    return text
```

In [10]: `data['processed'] = data['review'].apply(lambda x: clean_text(x))
data.head()`

Out [10]:

		review	sentiment	processed
0	One of the other reviewers has mentioned that ...	positive	one of the other reviewers has mentioned that ...	
1	A wonderful little production. The...	positive	a wonderful little production the filming tech...	
2	I thought this was a wonderful way to spend ti...	positive	i thought this was a wonderful way to spend ti...	
3	Basically there's a family where a little boy ...	negative	basically theres a family where a little boy j...	
4	Petter Mattei's "Love in the Time of Money" is...	positive	petter matteis love in the time of money is a ...	

In [11]: `bel' = data['sentiment'].apply(lambda x: 0 if x == 'negative' else

data[data['Label'] == 0]
data[data['Label'] == 1]

ze = int(0.7*25000)
= int(0.2*25000)

in = pd.concat((data_0[:train_size], data_1[:train_size]), axis = 0)
= pd.concat((data_0[train_size: (train_size + val_size)], data_1[train_size: (train_size + val_size)]), axis = 0)
t = pd.concat((data_0[(train_size + val_size):]), data_1[(train_size + val_size):])

y_train = list(data_train['processed']), np.array(data_train['Label'])
_val = list(data_val['processed']), np.array(data_val['Label'])
y_test = list(data_test['processed']), np.array(data_test['Label'])

rain size:', len(X_train))
alidation size: ', len(X_val))
est size: ', len(X_test))`

Train size: 35000
Validation size: 10000
Test size: 5000

```
In [14]: vocab_size = 10000
max_length = 500
trunc_type = 'post'
oov_tok = 'OOV'

from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences

# Tokenization
token = Tokenizer(num_words = vocab_size, oov_token = oov_tok)
token.fit_on_texts(X_train)
index_word = token.index_word

# Convert texts to sequences
train_seq = token.texts_to_sequences(X_train)
val_seq = token.texts_to_sequences(X_val)
test_seq = token.texts_to_sequences(X_test)

# Sequence padding
#Since the sequences have different lengtht, then we use padding me
#The parameter "maxlen" sets the maximum length of the output seque
#    + If length of the input sequence is larger than "maxlen", the
#    + If length of the input sequence is smaller than "maxlen", th

train_pad = pad_sequences(train_seq, maxlen = max_length, padding =
val_pad = pad_sequences(val_seq, maxlen = max_length, padding = 'po
test_pad = pad_sequences(test_seq, maxlen = max_length, padding = '
```

```
In [15]: # Shuffle the training set
p = np.random.permutation(len(train_pad))
train_pad = train_pad[p]
y_train = y_train[p]
```

```
In [17]:
```

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, Conv1D, AveragePooling1D
from tensorflow.keras.utils import plot_model

embedding_dim = 64

model = Sequential()
model.add(Embedding(vocab_size, embedding_dim, input_length = max_length))
model.add(Conv1D(filters = 32, kernel_size = 3, padding = 'same', activation = 'relu'))
model.add(AveragePooling1D(pool_size = 2))
model.add(Bidirectional(LSTM(200, dropout = 0.5)))
model.add(Dense(1, activation = 'sigmoid'))
model.compile(loss = 'binary_crossentropy', optimizer = 'adam', metrics = [accuracy])

plot_model(model, show_shapes = True)

H = model.fit(train_pad, y_train, epochs = 10, batch_size = 128,
               validation_data = (val_pad, y_val) )
```

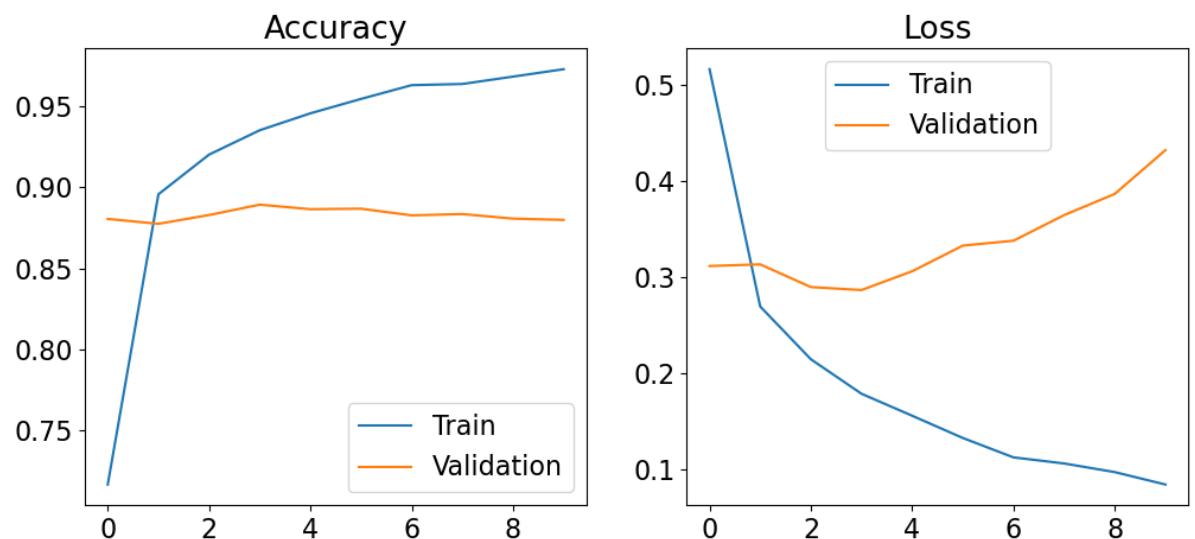
You must install pydot (`pip install pydot`) and install graphviz (see instructions at <https://graphviz.gitlab.io/download/> (<https://graphviz.gitlab.io/download/>)) for plot_model to work.

Epoch 1/10
274/274 [=====] - 960s 3s/step - loss: 0.5168 - accuracy: 0.7168 - val_loss: 0.3118 - val_accuracy: 0.8805
Epoch 2/10
274/274 [=====] - 968s 4s/step - loss: 0.2697 - accuracy: 0.8957 - val_loss: 0.3135 - val_accuracy: 0.8775
Epoch 3/10
274/274 [=====] - 982s 4s/step - loss: 0.2147 - accuracy: 0.9201 - val_loss: 0.2899 - val_accuracy: 0.8829
Epoch 4/10
274/274 [=====] - 984s 4s/step - loss: 0.1788 - accuracy: 0.9351 - val_loss: 0.2868 - val_accuracy: 0.8893
Epoch 5/10
274/274 [=====] - 985s 4s/step - loss: 0.1559 - accuracy: 0.9456 - val_loss: 0.3064 - val_accuracy: 0.8865
Epoch 6/10
274/274 [=====] - 989s 4s/step - loss: 0.1328 - accuracy: 0.9545 - val_loss: 0.3330 - val_accuracy: 0.8868
Epoch 7/10
274/274 [=====] - 988s 4s/step - loss: 0.1126 - accuracy: 0.9629 - val_loss: 0.3382 - val_accuracy: 0.8827
Epoch 8/10
274/274 [=====] - 972s 4s/step - loss: 0.1062 - accuracy: 0.9637 - val_loss: 0.3648 - val_accuracy: 0.8835
Epoch 9/10
274/274 [=====] - 967s 4s/step - loss: 0.0972 - accuracy: 0.9682 - val_loss: 0.3869 - val_accuracy: 0.8807
Epoch 10/10
274/274 [=====] - 966s 4s/step - loss: 0.0843 - accuracy: 0.9728 - val_loss: 0.4325 - val_accuracy: 0.8799

```
In [18]: plt.figure(figsize = (12,5))
plt.subplot(1,2,1)
plt.plot(H.history['accuracy'], label = 'Train')
plt.plot(H.history['val_accuracy'], label = 'Validation')
plt.legend()
plt.title('Accuracy')

plt.subplot(1,2,2)
plt.plot(H.history['loss'], label = 'Train')
plt.plot(H.history['val_loss'], label = 'Validation')
plt.legend()
plt.title('Loss')

plt.show()
```



```
In [19]: from sklearn.metrics import classification_report, confusion_matrix
y_pred_proba = model.predict(test_pad)
y_pred = np.array([0 if proba < 0.5 else 1 for proba in y_pred_proba])

print(classification_report(y_test, y_pred))

print('\n')

print('Balanced accuracy score: ', np.round(balanced_accuracy_score

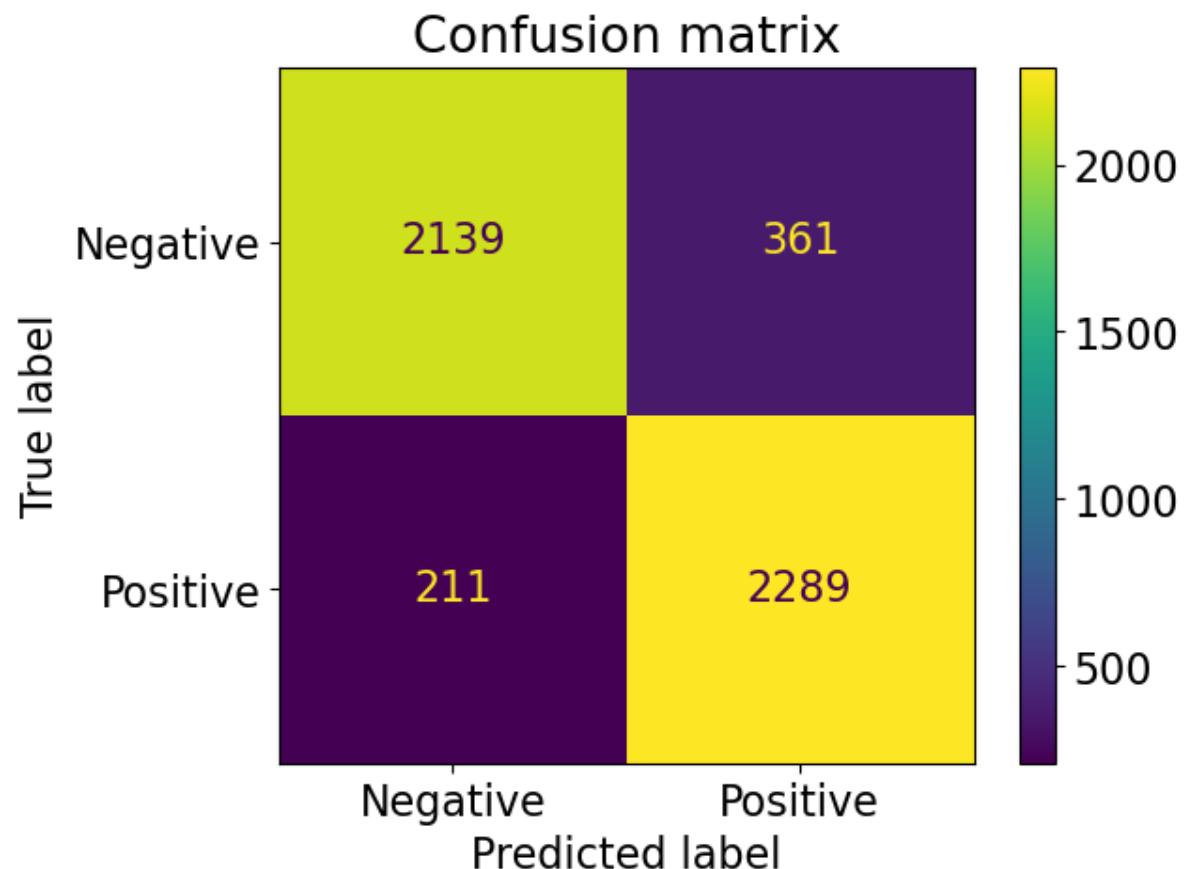
print('\n')
cm = ConfusionMatrixDisplay(confusion_matrix(y_test, y_pred), disp
plt.figure(figsize = (5,5))
cm.plot()
plt.title('Confusion matrix')
plt.show()
```

```
157/157 [=====] - 55s 337ms/step
      precision    recall   f1-score   support
          0       0.91      0.86      0.88      2500
          1       0.86      0.92      0.89      2500
```

accuracy			0.89	5000
macro avg	0.89	0.89	0.89	5000
weighted avg	0.89	0.89	0.89	5000

Balanced accuracy score: 0.89

<Figure size 500x500 with 0 Axes>



In []: