# Sentiment Analysis of IMDB Movie Reviews

In this, we have to predict the number of positive and negative reviews based on sentiments by using different classification models.

Dataset is taken from [https://www.kaggle.com/lakshmi25npathi/imdb-dataset-of-50k-movie-reviews](https://www.kaggle.com/lakshmi25npathi/imdb-dataset-of-50k-movie-reviews)

## IMPORT THE LIBRARIES

In [1]:
```
import pandas as pd
import numpy as np
```

In [2]:
```
import seaborn as sns
import matplotlib.pyplot as plt
import nltk
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.preprocessing import LabelBinarizer
from nltk.corpus import stopwords
from nltk.stem.porter import PorterStemmer
from wordcloud import WordCloud,STOPWORDS
from nltk.stem import WordNetLemmatizer
from nltk.tokenize import word_tokenize,sent_tokenize
from bs4 import BeautifulSoup
import spacy
import re,string,unicodedata
from nltk.tokenize.toktok import ToktokTokenizer
from nltk.stem import LancasterStemmer,WordNetLemmatizer
from sklearn.linear_model import LogisticRegression,SGDClassifier
from sklearn.naive_bayes import MultinomialNB
```

```
from sklearn.svm import SVC
from textblob import TextBlob
from textblob import Word
from sklearn.metrics import classification_report,confusion_matrix,accu
racy_score
```

# LOAD THE DATA

In [3]:
```
dataset=pd.read_csv('C:/Users/HP/Desktop/coursera/project/text_classifi
cation/IMDB Dataset.csv')
```

# EDA

View the dataset

In [4]:
```
dataset
```

Out[4]:

| | review | sentiment |
|---|---|---|
| 0 | One of the other reviewers has mentioned that ... | positive |
| 1 | A wonderful little production. <br /><br />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 |
| ... | ... | ... |
| 49995 | I thought this movie did a down right good job... | positive |
| 49996 | Bad plot, bad dialogue, bad acting, idiotic di... | negative |
| 49997 | I am a Catholic taught in parochial elementary... | negative |
| 49998 | I'm going to have to disagree with the previou... | negative |

| | review | sentiment |
|---|---|---|
| 49999 | No one expects the Star Trek movies to be high... | negative |

50000 rows × 2 columns

Get some information about the dataset

In [5]:
```
dataset.describe()
```

Out[5]:

| | review | sentiment |
|---|---|---|
| count | 50000 | 50000 |
| unique | 49582 | 2 |
| top | Loved today's show!!! It was a variety and not... | positive |
| freq | 5 | 25000 |

In [6]:
```
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50000 entries, 0 to 49999
Data columns (total 2 columns):
review       50000 non-null object
sentiment    50000 non-null object
dtypes: object(2)
memory usage: 781.4+ KB
```

Count the number of positive and negative reviews in the dataset

In [7]:
```
dataset['sentiment'].value_counts()
```

Out[7]:
```
positive    25000
negative    25000
Name: sentiment, dtype: int64
```

## TRAIN TEST SPLIT

In [8]:
```
X_train=dataset.review[:40000]
y_train=dataset.sentiment[:40000]
X_test=dataset.review[40000:]
y_test=dataset.review[40000:]
```

In [9]:
```
X_train
```

Out[9]:
```
0        One of the other reviewers has mentioned that ...
1        A wonderful little production. <br /><br />The...
2        I thought this was a wonderful way to spend ti...
3        Basically there's a family where a little boy ...
4        Petter Mattei's "Love in the Time of Money" is...
                               ...
39995    This was a marvelously funny comedy with a gre...
39996    There is no plot. There are no central charact...
39997    This show is awesome! I love all the actors! I...
39998    The fact that this movie has been entitled to ...
39999    I have to confess that I am severely disappoin...
Name: review, Length: 40000, dtype: object
```

In [10]:
```
X_train.shape
```

Out[10]:
```
(40000,)
```

In [11]:
```
y_train
```

Out[11]:
```
0        positive
1        positive
2        positive
3        negative
4        positive
           ...
39995    positive
39996    positive
39997    positive
```

```
39998    negative
39999    negative
Name: sentiment, Length: 40000, dtype: object
```

In [12]:
```
y_train.shape
```

Out[12]:
```
(40000,)
```

In [13]:
```
X_test
```

Out[13]:
```
40000    First off I want to say that I lean liberal on...
40001    I was excited to see a sitcom that would hopef...
40002    When you look at the cover and read stuff abou...
40003    Like many others, I counted on the appearance ...
40004    This movie was on t.v the other day, and I did...
                               ...
49995    I thought this movie did a down right good job...
49996    Bad plot, bad dialogue, bad acting, idiotic di...
49997    I am a Catholic taught in parochial elementary...
49998    I'm going to have to disagree with the previou...
49999    No one expects the Star Trek movies to be high...
Name: review, Length: 10000, dtype: object
```

In [14]:
```
X_test.shape
```

Out[14]:
```
(10000,)
```

In [15]:
```
y_test
```

Out[15]:
```
40000    First off I want to say that I lean liberal on...
40001    I was excited to see a sitcom that would hopef...
40002    When you look at the cover and read stuff abou...
40003    Like many others, I counted on the appearance ...
40004    This movie was on t.v the other day, and I did...
                               ...
49995    I thought this movie did a down right good job...
49996    Bad plot, bad dialogue, bad acting, idiotic di...
49997    I am a Catholic taught in parochial elementary...
```

```
49998    I'm going to have to disagree with the previou...
49999    No one expects the Star Trek movies to be high...
Name: review, Length: 10000, dtype: object
```

In [16]:
```
y_test.shape
```

Out[16]:
```
(10000,)
```

## Text normalization

In [17]:
```
tokenizer=ToktokTokenizer()
stopword_list=nltk.corpus.stopwords.words('english')
stopword_list
```

Out[17]:
```
['i',
 'me',
 'my',
 'myself',
 'we',
 'our',
 'ours',
 'ourselves',
 'you',
 "you're",
 "you've",
 "you'll",
 "you'd",
 'your',
 'yours',
 'yourself',
 'yourselves',
 'he',
 'him',
 'his',
 'himself',
 'she',
 "she's",
```

```
'her',
'hers',
'herself',
'it',
"it's",
'its',
'itself',
'they',
'them',
'their',
'theirs',
'themselves',
'what',
'which',
'who',
'whom',
'this',
'that',
"that'll",
'these',
'those',
'am',
'is',
'are',
'was',
'were',
'be',
'been',
'being',
'have',
'has',
'had',
'having',
'do',
'does',
'did',
'doing',
'a',
'an',
```

```
            'the',
            'and',
            'but',
            'if',
            'or',
            'because',
            'as',
            'until',
            'while',
            'of',
            'at',
            'by',
            'for',
            'with',
            'about',
            'against',
            'between',
            'into',
            'through',
            'during',
            'before',
            'after',
            'above',
            'below',
            'to',
            'from',
            'up',
            'down',
            'in',
            'out',
            'on',
            'off',
            'over',
            'under',
            'again',
            'further',
            'then',
            'once',
            'here',
```

```
'there',
'when',
'where',
'why',
'how',
'all',
'any',
'both',
'each',
'few',
'more',
'most',
'other',
'some',
'such',
'no',
'nor',
'not',
'only',
'own',
'same',
'so',
'than',
'too',
'very',
's',
't',
'can',
'will',
'just',
'don',
"don't",
'should',
"should've",
'now',
'd',
'll',
'm',
'o',
```

```
 're',
 've',
 'y',
 'ain',
 'aren',
 "aren't",
 'couldn',
 "couldn't",
 'didn',
 "didn't",
 'doesn',
 "doesn't",
 'hadn',
 "hadn't",
 'hasn',
 "hasn't",
 'haven',
 "haven't",
 'isn',
 "isn't",
 'ma',
 'mightn',
 "mightn't",
 'mustn',
 "mustn't",
 'needn',
 "needn't",
 'shan',
 "shan't",
 'shouldn',
 "shouldn't",
 'wasn',
 "wasn't",
 'weren',
 "weren't",
 'won',
 "won't",
 'wouldn',
 "wouldn't"]
```

## Removing html strips and noise text

### Removing the html strips

In [18]:
```
def strip_html(text):
    soup= BeautifulSoup(text,'html.parser')
    return soup.get_text()
```

### Removing the square brackets

In [19]:
```
def remove_between_square_brackets(text):
    return re.sub('\[[^]]*\]', '', text)
```

### Removing the noisy text

In [20]:
```
def denoise_text(text):
    text = strip_html(text)
    text = remove_between_square_brackets(text)
    return text
```

In [21]:
```
dataset['review']=dataset['review'].apply(denoise_text)
```

### Removing special characters

In [22]:
```
def remove_special_characters(text,remove_digits=True):
    pattern = r'[^a-zA-z0-9\s]'
    text=re.sub(pattern,'',text)
    return text
```

```
In [23]: dataset['review']=dataset['review'].apply(remove_special_characters)
```

### Text stemming

```
In [24]: def simple_stemmer(text):
             ps=nltk.porter.PorterStemmer()
             text= ' '.join([ps.stem(word) for word in text.split()])
             return text
```

```
In [25]: dataset['review']=dataset['review'].apply(simple_stemmer)
```

```
In [42]: #set stopwords to english
         stop=set(stopwords.words('english'))
         print(stop)

         #removing the stopwords
         def remove_stopwords(text, is_lower_case=False):
             tokens = tokenizer.tokenize(text)
             tokens = [token.strip() for token in tokens]
             if is_lower_case:
                 filtered_tokens = [token for token in tokens if token not in st
         opword_list]
             else:
                 filtered_tokens = [token for token in tokens if token.lower() n
         ot in stopword_list]
             filtered_text = ' '.join(filtered_tokens)
             return filtered_text

         #Apply function on review column
         dataset['review']=dataset['review'].apply(remove_stopwords)
```

```
{'than', "you'd", 'further', 've', 'nor', 'into', 'who', 'at', 'there',
'they', 'it', 'other', "don't", 'doesn', 'mightn', 'few', 'm', 'she',
'theirs', "you've", 'couldn', 'until', 'all', 'o', 'hers', 'ours', 'tha
t', 'll', 'haven', 'above', 'wasn', "you're", 'her', 'no', 'about', 'sh
ould', 'was', 'while', 'here', 'myself', 'our', 'same', 'will', 'what',
'but', 'these', 'a', 'off', 'to', 'up', 'ma', 'having', 'most', 'over',
```

```
'is', 'on', 'didn', 'when', 'through', "you'll", 'we', 't', 'ain', "mig
htn't", 'too', 'has', 'shouldn', 'itself', 'their', 'for', 'have', "sha
n't", "wasn't", 'ourselves', 'd', "won't", 'herself', "that'll", 'any',
'once', 'of', 'yourself', "didn't", "aren't", "hadn't", 'had', 'very',
'those', 'then', 'i', 'do', 'how', 'needn', 'me', 'during', 'under', 't
he', 'shan', 'this', 'him', 'were', 'being', 'himself', 'can', 'themsel
ves', 'be', 'did', 're', 'down', "haven't", 'its', 'against', 'not', "w
eren't", 'aren', 'before', 'why', "she's", 'isn', 'are', 'or', 'now',
"couldn't", 'mustn', "needn't", 'from', 'by', "doesn't", 'as', 'more',
'where', 'yourselves', "wouldn't", 'if', 'his', 'in', 'both', 'such',
'your', 'does', 'after', "should've", 'y', 'some', 'wouldn', 'own', 'yo
urs', 'which', 'hadn', "it's", 'so', 'just', 'doing', "shouldn't", "mus
tn't", 'because', 'won', 'my', 'weren', 'been', 'each', 'you', 'hasn',
'only', 'below', 'whom', 'with', 'don', 'them', 'he', "isn't", 'again',
'am', 'out', 'between', 's', "hasn't", 'an', 'and'}
```

### Normalized train reviews

In [26]:
```
norm_train_reviews=dataset.review[:40000]
norm_train_reviews[0]
```

Out[26]:
```
'one of the other review ha mention that after watch just 1 Oz episod y
oull be hook they are right as thi is exactli what happen with meth fir
st thing that struck me about Oz wa it brutal and unflinch scene of vio
lenc which set in right from the word GO trust me thi is not a show for
the faint heart or timid thi show pull no punch with regard to drug sex
or violenc it is hardcor in the classic use of the wordit is call OZ as
that is the nicknam given to the oswald maximum secur state penitentari
It focus mainli on emerald citi an experiment section of the prison whe
re all the cell have glass front and face inward so privaci is not high
on the agenda Em citi is home to manyaryan muslim gangsta latino christ
ian italian irish and moreso scuffl death stare dodgi deal and shadi ag
reement are never far awayi would say the main appeal of the show is du
e to the fact that it goe where other show wouldnt dare forget pretti p
ictur paint for mainstream audienc forget charm forget romanceoz doesnt
mess around the first episod I ever saw struck me as so nasti it wa sur
real I couldnt say I wa readi for it but as I watch more I develop a ta
st for Oz and got accustom to the high level of graphic violenc not jus
```

```
t violenc but injustic crook guard wholl be sold out for a nickel inmat
wholl kill on order and get away with it well manner middl class inmat
be turn into prison bitch due to their lack of street skill or prison e
xperi watch Oz you may becom comfort with what is uncomfort viewingthat
if you can get in touch with your darker side'
```

## Normalized test reviews

In [27]:

```
norm_test_reviews=dataset.review[40000:]
norm_test_reviews[45005]
```

Out[27]:

```
'I read all the review here after watch thi piec of cinemat garbag and
it took me at least 2 page to find out that somebodi els didnt think th
at thi appallingli unfunni montag wasnt the acm of humour in the 70 or
inde in ani other era If thi isnt the least funni set of sketch comedi
ive ever seen itll do till it come along half of the skit had alreadi b
een done and infinit better by act such as monti python and woodi allen
If I wa to say that a nice piec of anim that last about 90 second is th
e highlight of thi film it would still not get close to sum up just how
mindless and drivelridden thi wast of 75 minut is semin comedi onli in
the world where semin realli doe mean semen scatolog humour onli in a w
orld where scat IS actual fece precursor joke onli if by that we mean t
hat thi is a handbook of how not to do comedi tit and bum and the odd b
eaver niceif you are a pubesc boy with at least one hand free and haven
t found out that playboy exist give it a break becaus it wa the earli 7
0 No way there had been sketch comedi go back at least ten year prior t
he onli way I could even forgiv thi film even be made is if it wa at gu
npoint retro hardli sketch about clown subtli pervert children may be c
ut edg in some circl and it could actual have been funni but it just co
me off as realli quit sad what kept me go throughout the entir 75 minut
sheer belief that they may have save a genuin funni skit for the end I
gave the film a 1 becaus there wa no lower scoreand I can onli recommen
d it to insomniac or coma patientsor perhap peopl suffer from lockjawth
eir jaw would final drop open in disbelief'
```

## Bags of words model

In [28]:
```
#Count vectorizer for bag of words
cv=CountVectorizer(min_df=0,max_df=1,binary=False,ngram_range=(1,3))
#transformed train reviews
cv_train_reviews=cv.fit_transform(norm_train_reviews)
#transformed test reviews
cv_test_reviews=cv.transform(norm_test_reviews)

print('BOW_cv_train:',cv_train_reviews.shape)
print('BOW_cv_test:',cv_test_reviews.shape)
#vocab=cv.get_feature_names()-toget feature names
```

```
BOW_cv_train: (40000, 6030526)
BOW_cv_test: (10000, 6030526)
```

### Term Frequency-Inverse Document Frequency model (TFIDF)

In [29]:
```
tv=TfidfVectorizer(min_df=0,max_df=1,use_idf=True,ngram_range=(1,3))
#transformed train reviews
tv_train_reviews=tv.fit_transform(norm_train_reviews)
#transformed test reviews
tv_test_reviews=tv.transform(norm_test_reviews)
print('Tfidf_train:',tv_train_reviews.shape)
print('Tfidf_test:',tv_test_reviews.shape)
```

```
Tfidf_train: (40000, 6030526)
Tfidf_test: (10000, 6030526)
```

### Labeling the sentiment text

In [30]:
```
#labeling the sentient data
lb=LabelBinarizer()
#transformed sentiment data
sentiment_data=lb.fit_transform(dataset['sentiment'])
print(sentiment_data.shape)
```

```
(50000, 1)
```

### Split the sentiment tdata

In [31]:
```
#Spliting the sentiment data
train_sentiments=sentiment_data[:40000]
test_sentiments=sentiment_data[40000:]
print(train_sentiments)
print(test_sentiments)
```

```
[[1]
 [1]
 [1]
 ...
 [1]
 [0]
 [0]]
[[0]
 [0]
 [0]
 ...
 [0]
 [0]
 [0]]
```

### Modelling the dataset

In [32]:
```
#training the model
lr=LogisticRegression(penalty='l2',max_iter=500,C=1,random_state=42)
#Fitting the model for Bag of words
lr_bow=lr.fit(cv_train_reviews,train_sentiments)
print(lr_bow)
#Fitting the model for tfidf features
lr_tfidf=lr.fit(tv_train_reviews,train_sentiments)
print(lr_tfidf)
```

```
C:\Users\HP\Anaconda3\lib\site-packages\sklearn\utils\validation.py:72:
```

```
DataConversionWarning: A column-vector y was passed when a 1d array was
expected. Please change the shape of y to (n_samples, ), for example us
ing ravel().
  return f(**kwargs)
```

```
LogisticRegression(C=1, max_iter=500, random_state=42)
```

```
C:\Users\HP\Anaconda3\lib\site-packages\sklearn\utils\validation.py:72:
DataConversionWarning: A column-vector y was passed when a 1d array was
expected. Please change the shape of y to (n_samples, ), for example us
ing ravel().
  return f(**kwargs)
```

```
LogisticRegression(C=1, max_iter=500, random_state=42)
```

### Logistic regression model performane on test dataset

In [33]:

```
#Predicting the model for bag of words
lr_bow_predict=lr.predict(cv_test_reviews)
print(lr_bow_predict)
##Predicting the model for tfidf features
lr_tfidf_predict=lr.predict(tv_test_reviews)
print(lr_tfidf_predict)
```

```
[1 0 0 ... 0 0 1]
[1 0 0 ... 0 0 1]
```

### Accuracy of the model

In [34]:

```
#Accuracy score for bag of words
lr_bow_score=accuracy_score(test_sentiments,lr_bow_predict)
print("lr_bow_score :",lr_bow_score)
#Accuracy score for tfidf features
lr_tfidf_score=accuracy_score(test_sentiments,lr_tfidf_predict)
print("lr_tfidf_score :",lr_tfidf_score)
```

```
lr_bow_score : 0.7605
```

```
lr_tfidf_score : 0.7576
```

### Print the classification report

In [35]:
```
#Classification report for bag of words
lr_bow_report=classification_report(test_sentiments,lr_bow_predict,targ
et_names=['Positive','Negative'])
print(lr_bow_report)

#Classification report for tfidf features
lr_tfidf_report=classification_report(test_sentiments,lr_tfidf_predict,
target_names=['Positive','Negative'])
print(lr_tfidf_report)
```

```
              precision    recall  f1-score   support

    Positive       0.76      0.76      0.76      4993
    Negative       0.76      0.76      0.76      5007

    accuracy                           0.76     10000
   macro avg       0.76      0.76      0.76     10000
weighted avg       0.76      0.76      0.76     10000

              precision    recall  f1-score   support

    Positive       0.75      0.78      0.76      4993
    Negative       0.77      0.74      0.75      5007

    accuracy                           0.76     10000
   macro avg       0.76      0.76      0.76     10000
weighted avg       0.76      0.76      0.76     10000
```

### Confusion matrix

In [36]:
```
#confusion matrix for bag of words
```

```
cm_bow=confusion_matrix(test_sentiments,lr_bow_predict,labels=[1,0])
print(cm_bow)
#confusion matrix for tfidf features
cm_tfidf=confusion_matrix(test_sentiments,lr_tfidf_predict,labels=[1,0
])
print(cm_tfidf)
```

```
[[3821 1186]
 [1209 3784]]
[[3704 1303]
 [1121 3872]]
```

#### Stochastic gradient descent or Linear support vector machines for bag of words and tfidf features

In [37]:
```
#training the linear svm
svm=SGDClassifier(loss='hinge',max_iter=500,random_state=42)
#fitting the svm for bag of words
svm_bow=svm.fit(cv_train_reviews,train_sentiments)
print(svm_bow)
#fitting the svm for tfidf features
svm_tfidf=svm.fit(tv_train_reviews,train_sentiments)
print(svm_tfidf)
```

```
C:\Users\HP\Anaconda3\lib\site-packages\sklearn\utils\validation.py:72:
DataConversionWarning: A column-vector y was passed when a 1d array was
expected. Please change the shape of y to (n_samples, ), for example us
ing ravel().
  return f(**kwargs)
```

```
SGDClassifier(max_iter=500, random_state=42)
SGDClassifier(max_iter=500, random_state=42)
```

#### Model performance on test data

In [38]:
```
#Predicting the model for bag of words
```

```
svm_bow_predict=svm.predict(cv_test_reviews)
print(svm_bow_predict)
#Predicting the model for tfidf features
svm_tfidf_predict=svm.predict(tv_test_reviews)
print(svm_tfidf_predict)
```

```
[1 0 1 ... 0 1 1]
[1 1 1 ... 1 1 1]
```

### Accuracy of the model

In [39]:
```
#Accuracy score for bag of words
svm_bow_score=accuracy_score(test_sentiments,svm_bow_predict)
print("svm_bow_score :",svm_bow_score)
#Accuracy score for tfidf features
svm_tfidf_score=accuracy_score(test_sentiments,svm_tfidf_predict)
print("svm_tfidf_score :",svm_tfidf_score)
```

```
svm_bow_score : 0.6227
svm_tfidf_score : 0.5111
```

### Print the classification report

In [40]:
```
#Classification report for bag of words
svm_bow_report=classification_report(test_sentiments,svm_bow_predict,ta
rget_names=['Positive','Negative'])
print(svm_bow_report)
#Classification report for tfidf features
svm_tfidf_report=classification_report(test_sentiments,svm_tfidf_predic
t,target_names=['Positive','Negative'])
print(svm_tfidf_report)
```

```
              precision    recall  f1-score   support

    Positive       0.93      0.27      0.41      4993
    Negative       0.57      0.98      0.72      5007
```

```
    accuracy                           0.62     10000
   macro avg       0.75      0.62      0.57     10000
weighted avg       0.75      0.62      0.57     10000

              precision    recall  f1-score   support

    Positive       1.00      0.02      0.04      4993
    Negative       0.51      1.00      0.67      5007

    accuracy                           0.51     10000
   macro avg       0.75      0.51      0.36     10000
weighted avg       0.75      0.51      0.36     10000
```

### Plot the confusion matrix

In [41]:
```
#confusion matrix for bag of words
cm_bow=confusion_matrix(test_sentiments,svm_bow_predict,labels=[1,0])
print(cm_bow)
#confusion matrix for tfidf features
cm_tfidf=confusion_matrix(test_sentiments,svm_tfidf_predict,labels=[1,0
])
print(cm_tfidf)
```

```
[[4900  107]
 [3666 1327]]
[[5007    0]
 [4889  104]]
```

### Multinomial Naive Bayes for bag of words and tfidf features

In [42]:
```
#training the model
mnb=MultinomialNB()
#fitting the svm for bag of words
mnb_bow=mnb.fit(cv_train_reviews,train_sentiments)
```

```
print(mnb_bow)
#fitting the svm for tfidf features
mnb_tfidf=mnb.fit(tv_train_reviews,train_sentiments)
print(mnb_tfidf)
```

```
MultinomialNB()
```

```
C:\Users\HP\Anaconda3\lib\site-packages\sklearn\utils\validation.py:72:
DataConversionWarning: A column-vector y was passed when a 1d array was
expected. Please change the shape of y to (n_samples, ), for example us
ing ravel().
  return f(**kwargs)
```

```
MultinomialNB()
```

### Model performance on test data

In [43]:

```
#Predicting the model for bag of words
mnb_bow_predict=mnb.predict(cv_test_reviews)
print(mnb_bow_predict)
#Predicting the model for tfidf features
mnb_tfidf_predict=mnb.predict(tv_test_reviews)
print(mnb_tfidf_predict)
```

```
[1 0 0 ... 0 0 1]
[1 0 0 ... 0 0 1]
```

### Accuracy of the model

In [44]:

```
#Accuracy score for bag of words
mnb_bow_score=accuracy_score(test_sentiments,mnb_bow_predict)
print("mnb_bow_score :",mnb_bow_score)
#Accuracy score for tfidf features
mnb_tfidf_score=accuracy_score(test_sentiments,mnb_tfidf_predict)
print("mnb_tfidf_score :",mnb_tfidf_score)
```

```
mnb_bow_score : 0.7576
```

```
mnb_tfidf_score : 0.7572
```

#### Print the classification report

In [45]:
```
#Classification report for bag of words
mnb_bow_report=classification_report(test_sentiments,mnb_bow_predict,ta
rget_names=['Positive','Negative'])
print(mnb_bow_report)
#Classification report for tfidf features
mnb_tfidf_report=classification_report(test_sentiments,mnb_tfidf_predic
t,target_names=['Positive','Negative'])
print(mnb_tfidf_report)
```

```
              precision    recall  f1-score   support

    Positive       0.75      0.76      0.76      4993
    Negative       0.76      0.75      0.76      5007

    accuracy                           0.76     10000
   macro avg       0.76      0.76      0.76     10000
weighted avg       0.76      0.76      0.76     10000

              precision    recall  f1-score   support

    Positive       0.75      0.77      0.76      4993
    Negative       0.76      0.75      0.76      5007

    accuracy                           0.76     10000
   macro avg       0.76      0.76      0.76     10000
weighted avg       0.76      0.76      0.76     10000
```

#### Plot the confusion matrix

In [46]:
```
#confusion matrix for bag of words
cm_bow=confusion_matrix(test_sentiments,mnb_bow_predict,labels=[1,0])
```

```
print(cm_bow)
#confusion matrix for tfidf features
cm_tfidf=confusion_matrix(test_sentiments,mnb_tfidf_predict,labels=[1,0
])
print(cm_tfidf)
```

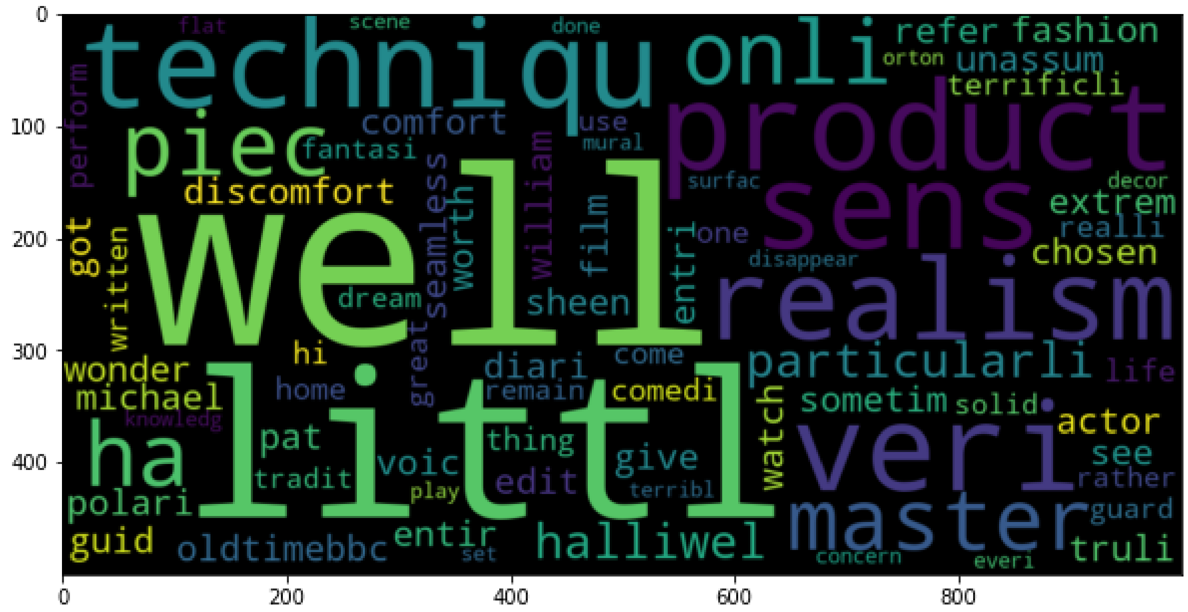
```
[[3762 1245]
 [1179 3814]]
[[3751 1256]
 [1172 3821]]
```

Let us see positive and negative words by using WordCloud

## Word cloud for positive review words

In [47]:
```
#word cloud for positive review words
plt.figure(figsize=(10,10))
positive_text=norm_train_reviews[1]
WC=WordCloud(width=1000,height=500,max_words=500,min_font_size=5)
positive_words=WC.generate(positive_text)
plt.imshow(positive_words,interpolation='bilinear')
plt.show
```

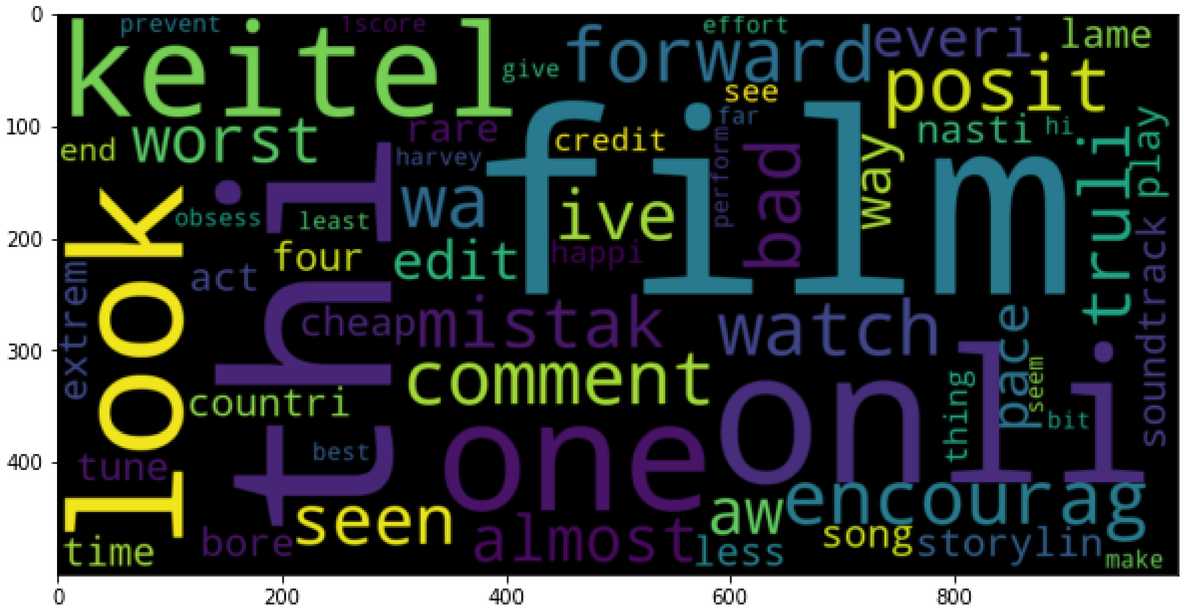
Out[47]:
```
<function matplotlib.pyplot.show(*args, **kw)>
```




### Word cloud for negative review words

In [48]:
```
#Word cloud for negative review words
plt.figure(figsize=(10,10))
negative_text=norm_train_reviews[8]
WC=WordCloud(width=1000,height=500,max_words=500,min_font_size=5)
negative_words=WC.generate(negative_text)
plt.imshow(negative_words,interpolation='bilinear')
plt.show
```

Out[48]:
```
<function matplotlib.pyplot.show(*args, **kw)>
```


0
100
200
300
400
0
200
400
600
800
prevent
iscore
effort
keitel
forward
everi
lame
give
posit
see
film
far
nasti
hi
worst
rare
credit
end
harvey
perform
bad
way
truli
play
thi
look
wa
ive
obsess
least
soundtrack
four
edit
happi
act
cheap
mistak
watch
extrem
comment
pace
seem
countri
onli
thing
bit
one
best
tune
seen
aw
encourag
almost
bore
song
time
less
storylin
make

In [ ]: