Task: To build a sentiment analysis model that can predict whether a movie review is positive or negative.

In [1]:
```
#first import necessary packages
import re
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from collections import Counter
import warnings
import nltk
from bs4 import BeautifulSoup

from sklearn.manifold import TSNE
from sklearn.metrics import accuracy_score, f1_score
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import LabelBinarizer
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer

stopwords= nltk.corpus.stopwords.words('english')
warnings.filterwarnings("ignore")
```

Step 1: Imported necessary libraries and packages.

In [2]:
```
#read the dataset
data = pd.read_csv('imdbds.csv')
data.head()
```

Out[2]:

	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

Step 2: Read the dataset using Pandas library. The first 5 rows are displayed to give a brief idea of the dataset.

In [3]:
```
data.info()
```

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

This gives information about the dataset; missing values can be identified here.

```
In [4]: print(data.describe())
        X=data['review']
        y=data['sentiment']
```

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

Step 3: An overall statistic is displayed here.

```
In [5]: def remove_special_characters(text):
            """Function to parse raw review data and extract
               text from it.
            """
            soup = BeautifulSoup(text, "html.parser")
            text = soup.get_text()
            text = re.sub('\[[^]]*\]', '', text)
            text = re.sub('[^a-zA-z0-9\s+\,]','',text)
            text = re.sub('\.{2,}','',text)
            return text

        def remove_stopwords(text):
            """Function to remove stopwords"""
            text = text.lower()
            words = text.split(" ")
            filtered_words = [i for i in words if i not in stopwords]
            filtered_words = ' '.join(filtered_words)
            return filtered_words

        class BuildVocab:
            """Class to build vocabulary for a given series of reviews and vocab size"""
            def __init__(self, sentences: pd.Series, vocab_size:int, unk_token=False):
                self.sentences = sentences
                self.vocab_size = vocab_size
                self.oov_token = unk_token

            def __process_sentences(self, sentence:str):
                sentence = re.sub(r'[^a-zA-Z\s+]', '', sentence).strip()
                return sentence
```

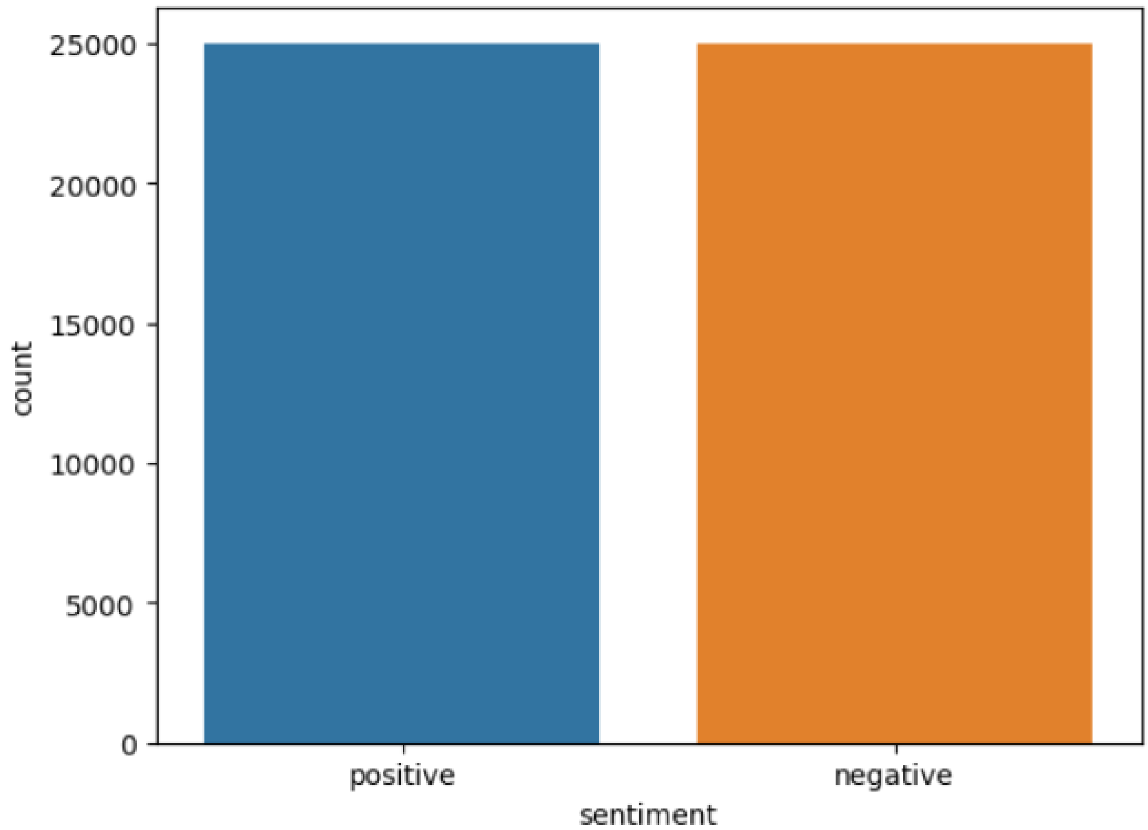
```
    def __sentence2words(self, sentence: str):
        word_list = list()
        for word in sentence.split(" "):
            if len(word) >= 1:
                word_list.append(word)
            else:
                pass
        return list(word_list)

    def __get_word_dictionary(self, sentences:list):
        words = list()
        for sentence in sentences:
            word_list = self.__sentence2words(sentence=sentence)
            words.extend(word_list)
        return list(words)

    def __get_topn_words(self, word_dictionary:dict):
        sorted_items = sorted(word_dictionary.items(), key=lambda item: item[1], reverse=True)
        top_n_words = [word for word, _ in sorted_items[:self.vocab_size]]
        return top_n_words


    def build(self):
        sentences = self.sentences.apply(self.__process_sentences)
        words = self.__get_word_dictionary(sentences=sentences.values)
        word_count_dict = Counter(words)
        vocab = self.__get_topn_words(word_dictionary=word_count_dict)

        if self.oov_token:
            vocab.append("UNK")
        else:
            pass

        index_dict = {x: index for x, index in zip(vocab, range(len(vocab)))}

        return vocab, index_dict
```

Step 4: These are some utilities that can be used in parsing the data and extracting words from it.

```
In [7]: print(f"Number of reviews: {len(X.values)}")
        sns.countplot(data=data, x="sentiment")
```

```
Number of reviews: 50000
```

```
Out[7]: <Axes: xlabel='sentiment', ylabel='count'>
```



Through this visualization we see that, the number of positive and negative reviews are equal.

```
In [8]: #cleaning and removing stopwords from reviews
        X = X.apply(remove_special_characters)
        X = X.apply(remove_stopwords)
```

```
In [9]: ## Building vocabulary with desired vocab size
        vocab, vocab_dict = BuildVocab(sentences=X, vocab_size=1000, unk_token=True).build()
```

```
In [10]: from sklearn.model_selection import train_test_split
         #splitting dataset into 75% train and 25% test set
         X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25,
                                                             random_state=0)
```

```
In [11]: tfidf = TfidfVectorizer(max_features = 500)
         tfidf = tfidf.fit(X_train)
         X_train, X_test = tfidf.transform(X_train), tfidf.transform(X_test)
```

```
In [12]: encoder = LabelBinarizer()
         encoder = encoder.fit(y_train)
         y_train,y_test = encoder.transform(y_train), encoder.transform(y_test)
         print(y_train.shape, y_test.shape)

(37500, 1) (12500, 1)
```

```
In [13]: lr = LogisticRegression(penalty="l2", max_iter=500, C=1, random_state=42)
         lr = lr.fit(X_train, y_train)
```

Step 5: Preparing the dataset and splitting it into test and train datasets.
Using TF-IDF for vectorization(TF-IDF: Term Frequency Inverse Document Frequency)
Assigns a single float value to a word relative to other words in the sentence and corpus.

Frequently occurring words will have lower value and rare words will have higher value hence higher importance.
It offers much better accuracy than the other methods of vectorization.
Used a logistic regression model to train.

In [14]:
```
#checking accuracy
train_pred = lr.predict(X_train)
test_pred = lr. predict(X_test)
train_acc = accuracy_score(y_train,train_pred)
print("Training accuracy: {}".format(train_acc))
test_acc = accuracy_score(y_test, test_pred)
print("Testing accuracy: {}".format(test_acc))
f1train = f1_score(y_train, train_pred)
print("F1 score(train): {}".format(f1train))
f1test = f1_score(y_test, test_pred)
print("F1 Score(test): {}".format(f1test))
```

```
Training accuracy: 0.8459466666666666
Testing accuracy: 0.83248
F1 score(train): 0.8477051643687555
F1 Score(test): 0.8331208160663054
```

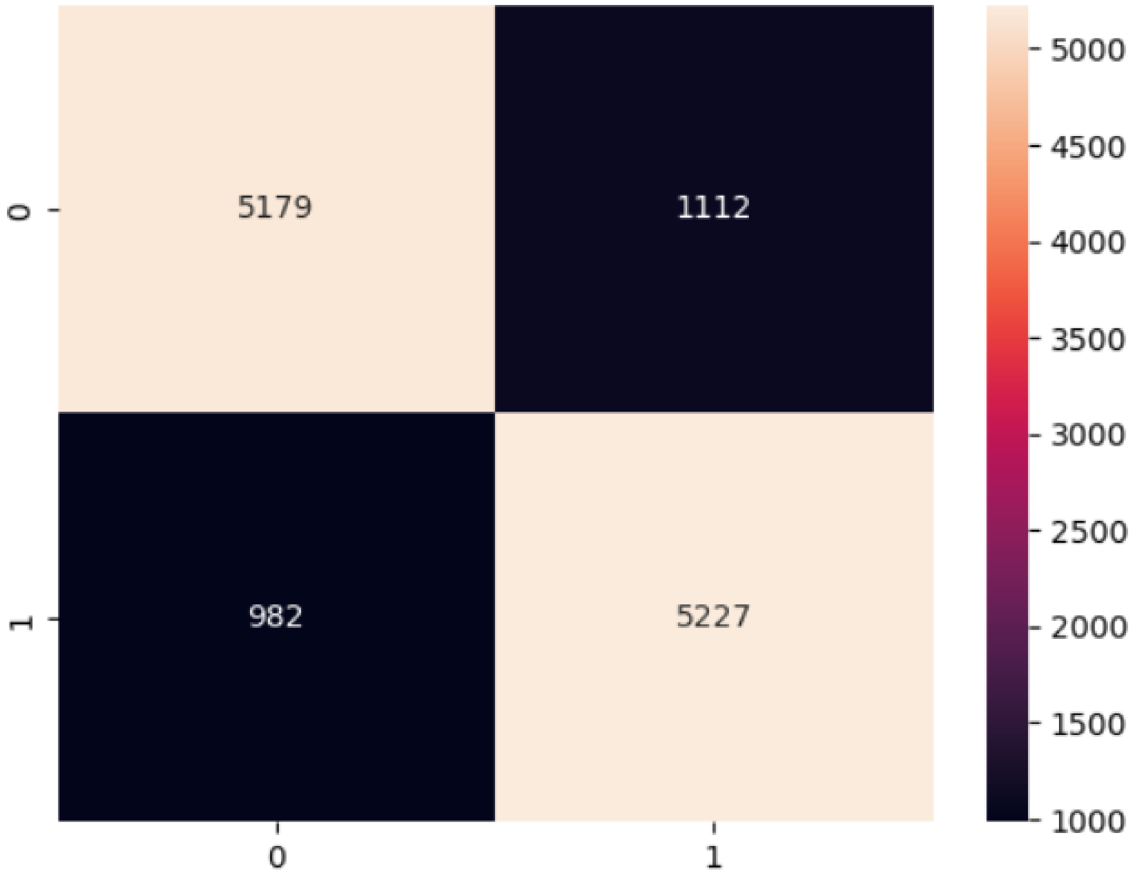
In [15]:
```
from sklearn.metrics import classification_report
print(classification_report(y_test,test_pred))
```

```
              precision    recall  f1-score   support

           0       0.84      0.82      0.83      6291
           1       0.82      0.84      0.83      6209

    accuracy                           0.83     12500
   macro avg       0.83      0.83      0.83     12500
weighted avg       0.83      0.83      0.83     12500
```

Step 6: Check accuracy of the model along with the precision, recall and f1 score.

In [16]:
```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test,test_pred)
sns.heatmap(cm, fmt='d', annot=True)
```

Out[16]: <Axes: >



Confusion matrix which visualises the results.