1. Цель лабораторной работы:

Изучение разработки рекомендательных моделей

2. Задание:

1.Выбрать произвольный набор данных (датасет), предназначенный для построения рекомендательных моделей.

2.Опираясь на материалы лекции, сформировать рекомендации для одного пользователя (объекта) двумя произвольными способами.

3.Сравнить полученные рекомендации (если это возможно, то с применением метрик).

3. Ход выполнения работы

Импорт библиотек

In [111]:
```
import numpy as np
import pandas as pd
from typing import Dict
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics.pairwise import cosine_similarity, euclidean_distances, manhattan_distances
from surprise import SVD, Dataset, Reader
import seaborn as sns
import matplotlib.pyplot as plt
from matplotlib_venn import venn2
%matplotlib inline
sns.set(style="ticks")
```

Чтение данных

In [112]:
```
df_movies_all=pd.read_csv('movies.csv')
df_movies_all.head()
```

Out[112]:

	movieId	title	genres
0	1	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy
1	2	Jumanji (1995)	Adventure|Children|Fantasy
2	3	Grumpier Old Men (1995)	Comedy|Romance
3	4	Waiting to Exhale (1995)	Comedy|Drama|Romance
4	5	Father of the Bride Part II (1995)	Comedy

In [113]:
```
df_movies_all.shape
```

Out[113]: (9742, 3)

In [114]:
```
df_ratings=pd.read_csv('ratings.csv')
df_ratings.head()
```

Out[114]:

	userId	movieId	rating	timestamp
0	1	1	4.0	964982703
1	1	3	4.0	964981247
2	1	6	4.0	964982224
3	1	47	5.0	964983815
4	1	50	5.0	964982931

In [115]:
```
df_ratings.shape
```

Out[115]: (100836, 4)

In [116]:
```
# Оставляем только аниме, которые есть в df_rating
movie_ids = df_ratings[df_ratings['movieId'].notnull()]['movieId']
df_movie = df_movies_all[df_movies_all['movieId'].isin(movie_ids)]
```

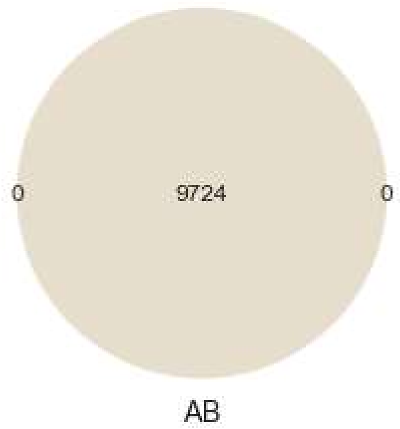
In [117]:
```
df_movies_all.shape,df_movie.shape
```

Out[117]:
```
((9742, 3), (9724, 3))
```

Выбор идентификаторов для связи таблиц

In [119]:
```
venn2([set(df_ratings['movieId'].unique()), set(df_movie['movieId'].unique())])
```

Out[119]:
```
<matplotlib_venn._common.VennDiagram at 0x276824ac0d0>
```



Векторизация описания фильмов

In [120]:
```
df_movie_with_genre = df_movie[df_movie['genres'].notnull()]
df_movie_with_genre = df_movie_with_genre[~df_movie_with_genre['genres'].str.isspace()]
```

In [121]:
```
movieId=df_movie_with_genre['movieId'].values
movieId[0:5]
```

Out[121]:
```
array([1, 2, 3, 4, 5], dtype=int64)
```

In [122]:
```
moviename=df_movie_with_genre['title'].values
moviename[0:5]
```

Out[122]:
```
array(['Toy Story (1995)', 'Jumanji (1995)', 'Grumpier Old Men (1995)',
       'Waiting to Exhale (1995)', 'Father of the Bride Part II (1995)'],
      dtype=object)
```

In [123]:
```
genre=df_movie_with_genre['genres'].values
genre[0:5]
```

Out[123]:
```
array(['Adventure|Animation|Children|Comedy|Fantasy',
       'Adventure|Children|Fantasy', 'Comedy|Romance',
       'Comedy|Drama|Romance', 'Comedy'], dtype=object)
```

In [124]:
```
%%time
tfidfv = TfidfVectorizer()
genre_matrix = tfidfv.fit_transform(genre)
genre_matrix
```

```
Wall time: 71 ms
```

Out[124]:
```
<9724x24 sparse matrix of type '<class 'numpy.float64'>'
	with 23179 stored elements in Compressed Sparse Row format>
```

3.1 Фильтрация на основе содержания

Рекомендации в зависимости от жанров аниме

In [125]:
```
class SimpleKNNRecommender:

    def __init__(self, X_matrix, X_ids, X_name, X_genre):
    # Входные параметры:
    # X_matrix - обучающая выборка (матрица объект-признак)
    # X_ids - массив идентификаторов
    # X_name - массив названий
    # X_genre - массив жанров

        self._X_matrix = X_matrix
        self.df = pd.DataFrame(
            {'id': pd.Series(X_ids, dtype='int'),
            'name': pd.Series(X_name, dtype='str'),
            'genre': pd.Series(X_genre, dtype='str'),
            'dist': pd.Series([], dtype='float')})


    def recommend_for_single_object(self, K: int, \
                X_matrix_object, cos_flag = True, manh_flag = False):
    # Метод формирования рекомендаций для одного объекта.
    # Входные параметры:
    # K - количество рекомендуемых соседей
    # X_matrix_object - строка матрицы объект-признак, соответствующая объекту
    # cos_flag - флаг вычисления косинусного расстояния
    # manh_flag - флаг вычисления манхэттэнского расстояния
    # Возвращаемое значение: K найденных соседей

        scale = 1000000
        # Вычисляем косинусную близость
        if cos_flag:
            dist = cosine_similarity(self._X_matrix, X_matrix_object)
            self.df['dist'] = dist * scale
            res = self.df.sort_values(by='dist', ascending=False)
            # Не учитываем рекомендации с единичным расстоянием,
            # так как это искомый объект
            res = res[res['dist'] < scale]

        else:
            if manh_flag:
                dist = manhattan_distances(self._X_matrix, X_matrix_object)
            else:
```

```
            dist = euclidean_distances(self._X_matrix, X_matrix_object)
        self.df['dist'] = dist * scale
        res = self.df.sort_values(by='dist', ascending=True)
        # Не учитываем рекомендации с единичным расстоянием,
        # так как это искомый объект
        res = res[res['dist'] > 0.0]

    # Оставляем K первых рекомендаций
    res = res.head(K)
    return res
```

In [126]:

```
Toy_Story  = 0
moviename[Toy_Story]
```

Out[126]: 'Toy Story (1995)'

In [127]:

```
genre[Toy_Story]
```

Out[127]: 'Adventure|Animation|Children|Comedy|Fantasy'

In [128]:

```
Toy_Story_matrix=genre_matrix[Toy_Story]
Toy_Story_matrix
```

Out[128]:

```
<1x24 sparse matrix of type '<class 'numpy.float64'>'
	with 5 stored elements in Compressed Sparse Row format>
```

In [129]:

```
skr1 = SimpleKNNRecommender(genre_matrix, movieId, moviename, genre)
```

In [130]:
```
rec1 = skr1.recommend_for_single_object(15, Toy_Story_matrix)
rec1
```

Out[130]:

	id	name	genre	dist
8882	134853	Inside Out (2015)	Adventure|Animation|Children|Comedy|Drama|Fantasy	970751.211229
4418	6536	Sinbad: Legend of the Seven Seas (2003)	Adventure|Animation|Children|Fantasy	963553.054623
5673	27731	Cat Returns, The (Neko no ongaeshi) (2002)	Adventure|Animation|Children|Fantasy	963553.054623
1576	2116	Lord of the Rings, The (1978)	Adventure|Animation|Children|Fantasy	963553.054623
9351	162578	Kubo and the Two Strings (2016)	Adventure|Animation|Children|Fantasy	963553.054623
1504	2033	Black Cauldron, The (1985)	Adventure|Animation|Children|Fantasy	963553.054623
6927	65261	Ponyo (Gake no ue no Ponyo) (2008)	Adventure|Animation|Children|Fantasy	963553.054623
4009	5672	Pokemon 4 Ever (a.k.a. Pokémon 4: The Movie) (...	Adventure|Animation|Children|Fantasy	963553.054623
3225	4366	Atlantis: The Lost Empire (2001)	Adventure|Animation|Children|Fantasy	963553.054623
2536	3400	We're Back! A Dinosaur's Story (1993)	Adventure|Animation|Children|Fantasy	963553.054623
5077	8015	Phantom Tollbooth, The (1970)	Adventure|Animation|Children|Fantasy	963553.054623
3331	4519	Land Before Time, The (1988)	Adventure|Animation|Children|Fantasy	963553.054623
9526	172793	Vovka in the Kingdom of Far Far Away (1965)	Adventure|Animation|Children|Fantasy	963553.054623
5611	27186	Kirikou and the Sorceress (Kirikou et la sorci...	Adventure|Animation|Children|Fantasy	963553.054623
6431	51939	TMNT (Teenage Mutant Ninja Turtles) (2007)	Action|Adventure|Animation|Children|Comedy|Fan...	939057.875775

In [131]:
```
rec2 = skr1.recommend_for_single_object(15, Toy_Story_matrix, cos_flag = False)
rec2
```

Out[131]:

	id	name	genre	dist
8882	134853	Inside Out (2015)	Adventure|Animation|Children|Comedy|Drama|Fantasy	241862.724582
1576	2116	Lord of the Rings, The (1978)	Adventure|Animation|Children|Fantasy	269988.686345
5611	27186	Kirikou and the Sorceress (Kirikou et la sorci...	Adventure|Animation|Children|Fantasy	269988.686345
5077	8015	Phantom Tollbooth, The (1970)	Adventure|Animation|Children|Fantasy	269988.686345
9526	172793	Vovka in the Kingdom of Far Far Away (1965)	Adventure|Animation|Children|Fantasy	269988.686345
1504	2033	Black Cauldron, The (1985)	Adventure|Animation|Children|Fantasy	269988.686345
9351	162578	Kubo and the Two Strings (2016)	Adventure|Animation|Children|Fantasy	269988.686345
4009	5672	Pokemon 4 Ever (a.k.a. Pokémon 4: The Movie) (...	Adventure|Animation|Children|Fantasy	269988.686345
3331	4519	Land Before Time, The (1988)	Adventure|Animation|Children|Fantasy	269988.686345
3225	4366	Atlantis: The Lost Empire (2001)	Adventure|Animation|Children|Fantasy	269988.686345
5673	27731	Cat Returns, The (Neko no ongaeshi) (2002)	Adventure|Animation|Children|Fantasy	269988.686345
2536	3400	We're Back! A Dinosaur's Story (1993)	Adventure|Animation|Children|Fantasy	269988.686345
4418	6536	Sinbad: Legend of the Seven Seas (2003)	Adventure|Animation|Children|Fantasy	269988.686345
6927	65261	Ponyo (Gake no ue no Ponyo) (2008)	Adventure|Animation|Children|Fantasy	269988.686345
6431	51939	TMNT (Teenage Mutant Ninja Turtles) (2007)	Action|Adventure|Animation|Children|Comedy|Fan...	349119.246747

In [132]:
```
rec3 = skr1.recommend_for_single_object(15, Toy_Story_matrix,
                                        cos_flag = False, manh_flag = True)
rec3
```

Out[132]:

	id	name	genre	dist
8882	134853	Inside Out (2015)	Adventure|Animation|Children|Comedy|Drama|Fantasy	304097.339211
9526	172793	Vovka in the Kingdom of Far Far Away (1965)	Adventure|Animation|Children|Fantasy	340177.899954
5077	8015	Phantom Tollbooth, The (1970)	Adventure|Animation|Children|Fantasy	340177.899954
2536	3400	We're Back! A Dinosaur's Story (1993)	Adventure|Animation|Children|Fantasy	340177.899954
1504	2033	Black Cauldron, The (1985)	Adventure|Animation|Children|Fantasy	340177.899954
3331	4519	Land Before Time, The (1988)	Adventure|Animation|Children|Fantasy	340177.899954
4418	6536	Sinbad: Legend of the Seven Seas (2003)	Adventure|Animation|Children|Fantasy	340177.899954
9351	162578	Kubo and the Two Strings (2016)	Adventure|Animation|Children|Fantasy	340177.899954
5611	27186	Kirikou and the Sorceress (Kirikou et la sorci...	Adventure|Animation|Children|Fantasy	340177.899954
3225	4366	Atlantis: The Lost Empire (2001)	Adventure|Animation|Children|Fantasy	340177.899954
5673	27731	Cat Returns, The (Neko no ongaeshi) (2002)	Adventure|Animation|Children|Fantasy	340177.899954
4009	5672	Pokemon 4 Ever (a.k.a. Pokémon 4: The Movie) (...	Adventure|Animation|Children|Fantasy	340177.899954
6927	65261	Ponyo (Gake no ue no Ponyo) (2008)	Adventure|Animation|Children|Fantasy	340177.899954
1576	2116	Lord of the Rings, The (1978)	Adventure|Animation|Children|Fantasy	340177.899954
5477	26340	Twelve Tasks of Asterix, The (Les douze travau...	Action|Adventure|Animation|Children|Comedy|Fan...	477128.215724

Как видите, все три метода вычисления расстояний дают правильные результаты. Рекомендуемые фильмы содержат ключевое слово того же типа.

3.2 Коллаборативная фильтрация

In [133]:
```
len(df_ratings['userId'].unique())# Количество уникальных пользователей
```
Out[133]:
```
610
```

In [134]:
```
len(df_ratings['movieId'].unique())# Количество уникальных аниме
```
Out[134]:
```
9724
```

In [135]:
```
def create_utility_matrix(data):
    itemField = 'movieId'
    userField = 'userId'
    valueField = 'rating'

    userList = data[userField].tolist()
    itemList = data[itemField].tolist()
    valueList = data[valueField].tolist()

    users = list(set(userList))
    items = list(set(itemList))

    users_index = {users[i]: i for i in range(len(users))}
    pd_dict = {item: [0.0 for i in range(len(users))] for item in items}

    for i in range(0,data.shape[0]):
        item = itemList[i]
        user = userList[i]
        value = valueList[i]
        pd_dict[item][users_index[user]] = value

    X = pd.DataFrame(pd_dict)
    X.index = users

    itemcols = list(X.columns)
    items_index = {itemcols[i]: i for i in range(len(itemcols))}

    return X, users_index, items_index
```

In [136]:
```
%%time
user_item_matrix, users_index, items_index = create_utility_matrix(df_ratings)
```

```
Wall time: 1.02 s
```

In [137]:
```
user_item_matrix
```

Out[137]:

	1	2	3	4	5	6	7	8	9	10	...	98239	98243	131013	131023	32728	163809	98279	32743	65514	98296
1	4.0	0.0	4.0	0.0	0.0	4.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5	4.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
606	2.5	0.0	0.0	0.0	0.0	0.0	2.5	0.0	0.0	0.0	...	0.0	3.0	0.0	0.0	4.0	0.0	0.0	0.0	0.0	0.0
607	4.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
608	2.5	2.0	2.0	0.0	0.0	0.0	0.0	0.0	0.0	4.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
609	3.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	4.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
610	5.0	0.0	0.0	0.0	0.0	5.0	0.0	0.0	0.0	0.0	...	2.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	4.0	0.0

610 rows × 9724 columns

Посмотрите, как пользователи оценили фильм 《Toy_Story》

In [138]:
```
print(df_ratings.loc[df_ratings['movieId']==1,['userId','rating']])
```

```
       userId  rating
0           1     4.0
516         5     4.0
874         7     4.5
1434       15     2.5
1667       17     4.5
...       ...     ...
97364     606     2.5
98479     607     4.0
98666     608     2.5
99497     609     3.0
99534     610     5.0

[215 rows x 2 columns]
```

Выбрать пользователей, которые дали 5 баллов для «Toy_Story», в качестве тестовых объектов для рекомендательной системы. Выбрать user_id = 610

In [139]:
```
user_item_matrix__test = user_item_matrix.loc[[610]]
user_item_matrix__test
```

Out[139]:

	1	2	3	4	5	6	7	8	9	10	...	98239	98243	131013	131023	32728	163809	98279	32743	65514	98296
610	5.0	0.0	0.0	0.0	0.0	5.0	0.0	0.0	0.0	0.0	...	2.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	4.0	0.0

1 rows × 9724 columns

In [140]:
```
user_item_matrix__train = user_item_matrix.loc[:609]
user_item_matrix__train
```

Out[140]:

	1	2	3	4	5	6	7	8	9	10	...	98239	98243	131013	131023	32728	163809	98279	32743	65514	98296
1	4.0	0.0	4.0	0.0	0.0	4.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5	4.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
605	4.0	3.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
606	2.5	0.0	0.0	0.0	0.0	0.0	2.5	0.0	0.0	0.0	...	0.0	3.0	0.0	0.0	4.0	0.0	0.0	0.0	0.0	0.0
607	4.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
608	2.5	2.0	2.0	0.0	0.0	0.0	0.0	0.0	0.0	4.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
609	3.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	4.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

609 rows × 9724 columns

Построение модели на основе SVD

In [141]:
```
%%time
U, S, VT = np.linalg.svd(user_item_matrix__train.T)
V = VT.T
```

```
Wall time: 3.82 s
```

In [142]:
```
U.shape# 用户和潜在因素之间的关系矩阵
```

Out[142]:
```
(9724, 9724)
```

In [143]:
```
V.shape# 对象和潜在因素之间的关系矩阵
```

Out[143]:
```
(609, 609)
```

In [144]:
```
S.shape
```

Out[144]:
```
(609,)
```

In [145]:
```
Sigma = np.diag(S)# 对角奇异值矩阵
Sigma.shape
```

Out[145]:
```
(609, 609)
```

In [146]:
```
Sigma
```

Out[146]:
```
array([[529.4937201 ,   0.        ,   0.        , ...,   0.        ,
          0.        ,   0.        ],
       [  0.        , 227.50885376,   0.        , ...,   0.        ,
          0.        ,   0.        ],
       [  0.        ,   0.        , 190.53715518, ...,   0.        ,
          0.        ,   0.        ],
       ...,
       [  0.        ,   0.        ,   0.        , ...,   3.87425933,
          0.        ,   0.        ],
       [  0.        ,   0.        ,   0.        , ...,   0.        ,
          3.11412817,   0.        ],
       [  0.        ,   0.        ,   0.        , ...,   0.        ,
          0.        ,   2.9480028 ]])
```

In [147]:
```
r=3
Ur = U[:, :r]
Sr = Sigma[:r, :r]
Vr = V[:, :r]
```

In [148]:
```
# 新用户和潜在因素之间的关系矩阵
test_user = np.mat(user_item_matrix__test.values)
test_user.shape, test_user
```

Out[148]:
```
((1, 9724), matrix([[5., 0., 0., ..., 0., 4., 0.]]))
```

In [149]:
```
tmp = test_user * Ur * np.linalg.inv(Sr)
tmp
```

Out[149]:
```
matrix([[-0.13331135,  0.15981166, -0.0692074 ]])
```

In [150]:
```
test_user_result = np.array([tmp[0,0], tmp[0,1], tmp[0,2]])
test_user_result
```

Out[150]:
```
array([-0.13331135,  0.15981166, -0.0692074 ])
```

In [151]:
```
cos_sim = cosine_similarity(Vr, test_user_result.reshape(1, -1))
cos_sim[:10]
```

Out[151]:
```
array([[-0.15984579],
       [ 0.81159541],
       [-0.14714827],
       [-0.13610433],
       [-0.44311623],
       [-0.47390031],
       [ 0.48528426],
       [-0.41232427],
       [ 0.78471551],
       [ 0.8713775 ]])
```

In [152]:
```
cos_sim_list = cos_sim.reshape(-1, cos_sim.shape[0])[0]
cos_sim_list[:10]
```

Out[152]:
```
array([-0.15984579,  0.81159541, -0.14714827, -0.13610433, -0.44311623,
       -0.47390031,  0.48528426, -0.41232427,  0.78471551,  0.8713775 ])
```

In [153]:
```
recommended_user_id = np.argsort(-cos_sim_list)[0]
recommended_user_id
```

Out[153]:
```
317
```

In [154]:
```
df_movie
```

Out[154]:

	movieId	title	genres
0	1	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy
1	2	Jumanji (1995)	Adventure|Children|Fantasy
2	3	Grumpier Old Men (1995)	Comedy|Romance
3	4	Waiting to Exhale (1995)	Comedy|Drama|Romance
4	5	Father of the Bride Part II (1995)	Comedy
...	...	...	...
9737	193581	Black Butler: Book of the Atlantic (2017)	Action|Animation|Comedy|Fantasy
9738	193583	No Game No Life: Zero (2017)	Animation|Comedy|Fantasy
9739	193585	Flint (2017)	Drama
9740	193587	Bungo Stray Dogs: Dead Apple (2018)	Action|Animation
9741	193609	Andrew Dice Clay: Dice Rules (1991)	Comedy

9724 rows × 3 columns

In [155]:
```
movie_list = list(user_item_matrix.columns)
def movie_recommend(ind):
    try:
        movie_id = movie_list[ind]
        flt_rating = df_ratings[df_ratings['movieId'] == movie_id ]
        rating = flt_rating['movieId'].values[0]
        moive_rating = df_movie[df_movie['movieId'] == rating]
        res = moive_rating['title'].values[0]
        return res
    except:
        return ''
```

In [156]:
```
# Аниме, которые оценивал текущий пользователь user_id=152:
i=1
for idx, item in enumerate(np.ndarray.flatten(np.array(test_user))):
    if item > 0:
        movie_name = movie_recommend(idx)
        print('{} - {} - {}'.format(idx,movie_name, item))
        if i==20:
            break
        else:
            i+=1
```

```
0 - Toy Story (1995) - 5.0
5 - Heat (1995) - 5.0
15 - Casino (1995) - 4.5
31 - Twelve Monkeys (a.k.a. 12 Monkeys) (1995) - 4.5
46 - Seven (a.k.a. Se7en) (1995) - 5.0
49 - Usual Suspects, The (1995) - 4.0
69 - From Dusk Till Dawn (1996) - 4.0
92 - Broken Arrow (1996) - 3.5
107 - Braveheart (1995) - 4.5
108 - Taxi Driver (1976) - 5.0
109 - Rumble in the Bronx (Hont faan kui) (1995) - 4.0
132 - 31 (2016) - 3.5
142 - Batman Forever (1995) - 3.0
148 - Clockers (1995) - 3.5
182 - Smoke (1995) - 5.0
185 - Fearless Hyena, The (Xiao quan guai zhao) (1979) - 3.0
203 - Before Sunrise (1995) - 5.0
218 - Dumb & Dumber (Dumb and Dumber) (1994) - 4.0
225 - Hitchhiker's Guide to the Galaxy, The (2005) - 3.5
247 - Star Wars: Episode IV - A New Hope (1977) - 5.0
```

In [157]:
```
# Аниме, которые оценивал наиболее схожий пользователь:
i=1
recommended_user_item_matrix = user_item_matrix.loc[[recommended_user_id+1]]
for idx, item in enumerate(np.ndarray.flatten(np.array(recommended_user_item_matrix))):
    if item > 0:
        movie_name = movie_recommend(idx)
        print('{} - {} - {}'.format(idx, movie_name, item))
        if i==20:
            break
        else:
            i+=1
```

```
1 - Jumanji (1995) - 3.5
5 - Heat (1995) - 4.0
17 - Four Rooms (1995) - 3.0
18 - Ace Ventura: When Nature Calls (1995) - 3.5
28 - City of Lost Children, The (Cité des enfants perdus, La) (1995) - 3.5
31 - Twelve Monkeys (a.k.a. 12 Monkeys) (1995) - 4.5
46 - Seven (a.k.a. Se7en) (1995) - 4.0
47 - Pocahontas (1995) - 3.5
71 - Kicking and Screaming (1995) - 4.5
93 - Battle in Seattle (2007) - 4.0
94 - Hate (Haine, La) (1995) - 4.5
106 - Timecrimes (Cronocrímenes, Los) (2007) - 3.5
119 - Chungking Express (Chung Hing sam lam) (1994) - 4.5
125 - Trip to the Moon, A (Voyage dans la lune, Le) (1902) - 3.0
129 - Ascent, The (Voskhozhdeniye) (1977) - 3.5
134 - Bad Boys (1995) - 3.5
142 - Batman Forever (1995) - 3.0
143 - Beauty of the Day (Belle de jour) (1967) - 3.0
148 - Clockers (1995) - 4.0
151 - Crumb (1994) - 3.5
```