Московский государственный технический университет им. Н.Э.

Баумана Кафедра «Системы обработки информации и управления»

Лабораторная работа №1

по дисциплине

«Методы машинного обучения»

на тему

«Создание рекомендательной модели»

Выполнил:

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1. Цель лабораторной работы

изучение разработки рекомендательных моделей.

2. Задание

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

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

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

3. Ход выполнения работы

Подключим все необходимые библиотеки и настроим отображение графиков:

In [1]:
```python
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")
```

загрузите набор данных:

```
In [2]: df=pd.read_csv('books.csv')
```

```
In [3]: df.head()
```

Out[3]:

	id	book_id	best_book_id	work_id	books_count	isbn	isbn13	authors	original_publication_year	original_title	...	ratings_count	work_rating
0	1	2767052	2767052	2792775	272	439023483	9.780439e+12	Suzanne Collins	2008.0	The Hunger Games	...	4780653	
1	2	3	3	4640799	491	439554934	9.780440e+12	J.K. Rowling, Mary GrandPré	1997.0	Harry Potter and the Philosopher's Stone	...	4602479	
2	3	41865	41865	3212258	226	316015849	9.780316e+12	Stephenie Meyer	2005.0	Twilight	...	3866839	
3	4	2657	2657	3275794	487	61120081	9.780061e+12	Harper Lee	1960.0	To Kill a Mockingbird	...	3198671	
4	5	4671	4671	245494	1356	743273567	9.780743e+12	F. Scott Fitzgerald	1925.0	The Great Gatsby	...	2683664	

5 rows × 23 columns

```
In [4]: df.shape
Out[4]: (10000, 23)
```

```
In [5]: rating=pd.read_csv('ratings.csv')
```

```
In [6]: rating.head()
```

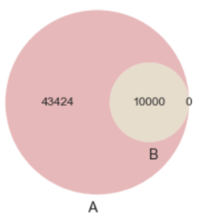
Out[6]:

	book_id	user_id	rating
0	1	314	5
1	1	439	3
2	1	588	5
3	1	1169	4
4	1	1185	4

```
In [7]: rating.shape
Out[7]: (981756, 3)
```

```
In [15]: venn2([set(rating['book_id'].unique()), set(df['book_id'].unique())])
Out[15]: <matplotlib_venn._common.VennDiagram at 0x14baef15250>
```


```
In [14]: venn2([set(rating['user_id'].unique()), set(df['id'].unique())])
Out[14]: <matplotlib_venn._common.VennDiagram at 0x14baef50f10>
```



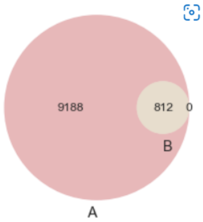
оставить только book_id:

```
In [21]: book_ids=rating[rating['book_id'].notnull()]['book_id']
         df_book = df[df['book_id'].isin(book_ids)]
```

```
In [22]: df.shape, df_book.shape
Out[22]: ((10000, 23), (812, 23))
```

Выбор идентификаторов для связи таблиц:

In [23]:
```
venn2([set(rating['book_id'].unique()), set(df_book['book_id'].unique())])
```
Out[23]: <matplotlib_venn._common.VennDiagram at 0x14baefc1430>



Векторизация описания книг

In [26]:
```
df_book_author = df_book[df_book['authors'].notnull()]
df_book_author = df_book_author[~df_book_author['authors'].str.isspace()]
```

In [27]:
```
book_id=df_book_author['book_id'].values
book_id[0:5]
```
Out[27]:
```
array([   3, 2657, 4671, 5907, 5107], dtype=int64)
```

In [28]:
```
book_name=df_book_author['original_title'].values
book_name[0:5]
```
Out[28]:
```
array(["Harry Potter and the Philosopher's Stone",
       'To Kill a Mockingbird', 'The Great Gatsby',
       'The Hobbit or There and Back Again', 'The Catcher in the Rye'],
      dtype=object)
```

In [29]:
```
author=df_book_author['authors'].values
author[0:5]
```
Out[29]:
```
array(['J.K. Rowling, Mary GrandPré', 'Harper Lee', 'F. Scott Fitzgerald',
       'J.R.R. Tolkien', 'J.D. Salinger'], dtype=object)
```

In [31]:
```
language=df_book_author['language_code'].values
language[0:5]
```
Out[31]:
```
array(['eng', 'eng', 'eng', 'en-US', 'eng'], dtype=object)
```

In [32]:
```
%%time
tfidfv = TfidfVectorizer()
author_matrix = tfidfv.fit_transform(author)
author_matrix
```
```
CPU times: total: 0 ns
Wall time: 19 ms
```
Out[32]:
```
<812x1020 sparse matrix of type '<class 'numpy.float64'>'
	with 2313 stored elements in Compressed Sparse Row format>
```

3.1 Фильтрация на основе содержания

Рекомендации на основе авторов

In [48]:
```
class SimpleKNNRecommender:

    def __init__(self, X_matrix, X_ids, X_name, X_author, X_language):

        self._X_matrix = X_matrix
        self.df = pd.DataFrame(
            {'id': pd.Series(X_ids, dtype='int'),
            'name': pd.Series(X_name, dtype='str'),
            'author': pd.Series(X_author, dtype='str'),
            'language':pd.Series(X_language,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 [49]:
```
Harry_Potter=0
book_name[Harry_Potter]
```

Out[49]: "Harry Potter and the Philosopher's Stone"

In [50]:
```
author[Harry_Potter]
```

Out[50]: 'J.K. Rowling, Mary GrandPré'

In [51]:
```
Harry_Potter_matrix=author_matrix[Harry_Potter]
Harry_Potter_matrix
```

Out[51]:
```
<1x1020 sparse matrix of type '<class 'numpy.float64'>'
        with 3 stored elements in Compressed Sparse Row format>
```

In [53]:
```
skr1 = SimpleKNNRecommender(author_matrix, book_id, book_name, author, language)
rec1 = skr1.recommend_for_single_object(15,Harry_Potter_matrix)
rec1
```

Out[53]:

	id	name	author	language	dist
9	5	Harry Potter and the Prisoner of Azkaban	J.K. Rowling, Mary GrandPré, Rufus Beck	eng	698734.891897
773	2002	NaN	J.K. Rowling	eng	568566.112224
505	10	Harry Potter Collection (Harry Potter, #1-6)	J.K. Rowling	eng	568566.112224
726	8646	Crow Lake	Mary Lawson	eng	351175.639858
510	5182	Songs in Ordinary Time	Mary McGarry Morris	eng	276036.886797
535	1426	Manual do guerreiro da luz	Paulo Coelho	en-US	0.000000
536	6572	Suffer the Children	John Saul	en-US	0.000000
537	36	The Lord of the Rings: Weapons and Warfare	Chris Smith, Christopher Lee, Richard Taylor	eng	0.000000
538	7194	El club Dumas	Arturo Pérez-Reverte, Sonia Soto	eng	0.000000
539	3378	Generation X: Tales for an Accelerated Culture	Douglas Coupland	eng	0.000000
540	7036	The Kalahari Typing School for Men	Alexander McCall Smith	eng	0.000000
541	4600	Moo, Baa, La La La!	Sandra Boynton	eng	0.000000
542	880	Pompeii	Robert Harris	eng	0.000000
543	5693	Рассказы и Повести	Anton Chekhov, Richard Pevear, Larissa Volokho...	eng	0.000000
544	668	We the Living	Ayn Rand, Leonard Peikoff	eng	0.000000

In [54]:
```
rec2 = skr1.recommend_for_single_object(15, Harry_Potter_matrix, cos_flag = False)
rec2
```

Out[54]:

	id	name	author	language	dist
9	5	Harry Potter and the Prisoner of Azkaban	J.K. Rowling, Mary GrandPré, Rufus Beck	eng	7.762282e+05
505	10	Harry Potter Collection (Harry Potter, #1-6)	J.K. Rowling	eng	9.289068e+05
773	2002	NaN	J.K. Rowling	eng	9.289068e+05
726	8646	Crow Lake	Mary Lawson	eng	1.139144e+06
510	5182	Songs in Ordinary Time	Mary McGarry Morris	eng	1.203298e+06
467	4035	The Burden of Proof	Scott Turow	eng	1.414214e+06
493	6462	His Excellency: George Washington	Joseph J. Ellis	eng	1.414214e+06
462	6862	Amsterdam	Ian McEwan	NaN	1.414214e+06
496	415	Gravity's Rainbow	Thomas Pynchon	eng	1.414214e+06
497	3686	Truth & Beauty: A Friendship	Ann Patchett	eng	1.414214e+06
498	597	Killing Yourself to Live: 85% of a True Story	Chuck Klosterman	en-US	1.414214e+06
499	9589	Hocus Pocus	Kurt Vonnegut Jr.	NaN	1.414214e+06
492	4820	Mayflower: A Story of Courage, Community, and War	Nathaniel Philbrick	eng	1.414214e+06
500	6748	A Supposedly Fun Thing I'll Never Do Again: Es...	David Foster Wallace	en-GB	1.414214e+06
502	9820	Crossing to Safety	Wallace Stegner	eng	1.414214e+06

In [55]:
```
rec3 = skrl.recommend_for_single_object(15, Harry_Potter_matrix,
                                        cos_flag = False, manh_flag = True)
rec3
```

Out[55]:

	id	name	author	language	dist
9	5	Harry Potter and the Prisoner of Azkaban	J.K. Rowling, Mary GrandPré, Rufus Beck	eng	1.533390e+06
773	2002	NaN	J.K. Rowling	eng	1.594529e+06
505	10	Harry Potter Collection (Harry Potter, #1-6)	J.K. Rowling	eng	1.594529e+06
726	8646	Crow Lake	Mary Lawson	eng	1.998633e+06
510	5182	Songs in Ordinary Time	Mary McGarry Morris	eng	2.482525e+06
441	4538	The View from Saturday	E.L. Konigsburg	NaN	2.731662e+06
352	3102	Howards End	E.M. Forster	eng	2.731662e+06
304	6192	Disgrace	J.M. Coetzee	eng	2.731662e+06
234	3579	The Complete Anne of Green Gables Boxed Set	L.M. Montgomery	NaN	2.731662e+06
211	3087	A Room with a View	E.M. Forster	eng	2.731662e+06
202	3980	From the Mixed-Up Files of Mrs. Basil E. Frank...	E.L. Konigsburg	eng	2.731662e+06
446	4921	Three Men in a Boat (To Say Nothing of the Dog)	Jerome K. Jerome	eng	2.731662e+06
546	9784	Women in Love	D.H. Lawrence	eng	2.731662e+06
520	3562	Emily of New Moon	L.M. Montgomery	eng	2.731662e+06
56	8127	Anne of Green Gables	L.M. Montgomery	eng	2.731662e+06

Можно увидеть,все три расчета расстояния дают правильные результаты.

3.2 Коллаборативная фильтрация

In [56]:
```
len(rating['user_id'].unique())
```

Out[56]: 53424

In [57]:
```
len(rating['book_id'].unique())
```

Out[57]: 10000

In [58]:
```python
def create_utility_matrix(data):
    itemField = 'book_id'
    userField = 'user_id'
    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 [59]:
```python
%%time
user_item_matrix, users_index, items_index = create_utility_matrix(rating)
```

```
CPU times: total: 1min 51s
Wall time: 2min 3s
```

In [60]:
```python
user_item_matrix
```

Out[60]:

	1	2	3	4	5	6	7	8	9	10	...	9991	9992	9993	9994	9995	9996	9997	9998	9999	10000
1	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
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	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
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
53420	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
53421	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
53422	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
53423	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
53424	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

53424 rows × 10000 columns

Проверьте пользователей, которые оценили книги «Harry_Potter»

In [61]:
```python
print(rating.loc[rating['book_id']==3,['user_id','rating']])
```

```
     user_id  rating
200      314       3
201      588       1
202     2077       2
203     2487       3
204     2900       3
..       ...     ...
295    50133       5
296    51166       3
297    51460       2
298    52036       1
299    53292       5

[100 rows x 2 columns]
```

Выбрать пользователей, которые дали 5 баллов для «Harry_Potter», в качестве тестовых объектов для рекомендательной системы.

Выбрать user_id = 50133.

In [62]:
```
user_item_matrix__test = user_item_matrix.loc[[50133]]
user_item_matrix__test
```

Out[62]:

	1	2	3	4	5	6	7	8	9	10	...	9991	9992	9993	9994	9995	9996	9997	9998	9999	10000
50133	0.0	5.0	5.0	0.0	0.0	5.0	0.0	5.0	0.0	5.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

1 rows × 10000 columns

In [63]:
```
user_item_matrix__train = user_item_matrix.loc[:53424]
user_item_matrix__train
```

Out[63]:

	1	2	3	4	5	6	7	8	9	10	...	9991	9992	9993	9994	9995	9996	9997	9998	9999	10000
1	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
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	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
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
53420	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
53421	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
53422	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
53423	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
53424	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

53424 rows × 10000 columns

Построение модели на основе SVD

In [65]:
```
user_item_matrix__train = user_item_matrix.loc[:1000]
user_item_matrix__train
```

Out[65]:

	1	2	3	4	5	6	7	8	9	10	...	9991	9992	9993	9994	9995	9996	9997	9998	9999	10000
1	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
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	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
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
996	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
997	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
998	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
999	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
1000	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

1000 rows × 10000 columns

```
%%time
U, S, VT = np.linalg.svd(user_item_matrix__train.T)
V = VT.T
```

```
CPU times: total: 25.8 s
Wall time: 7.09 s
```

```
U.shape
```

```
(10000, 10000)
```

```
V.shape
```

```
(1000, 1000)
```

```
S.shape
```

```
(1000,)
```

```
Sigma = np.diag(S)
Sigma.shape
```

```
(1000, 1000)
```

```
Sigma
```

```
array([[6.78501113e+01, 0.00000000e+00, 0.00000000e+00, ...,
        0.00000000e+00, 0.00000000e+00, 0.00000000e+00],
       [0.00000000e+00, 5.70177294e+01, 0.00000000e+00, ...,
        0.00000000e+00, 0.00000000e+00, 0.00000000e+00],
       [0.00000000e+00, 0.00000000e+00, 5.25771171e+01, ...,
        0.00000000e+00, 0.00000000e+00, 0.00000000e+00],
       ...,
       [0.00000000e+00, 0.00000000e+00, 0.00000000e+00, ...,
        2.75272997e-15, 0.00000000e+00, 0.00000000e+00],
       [0.00000000e+00, 0.00000000e+00, 0.00000000e+00, ...,
        0.00000000e+00, 2.53386923e-15, 0.00000000e+00],
       [0.00000000e+00, 0.00000000e+00, 0.00000000e+00, ...,
        0.00000000e+00, 0.00000000e+00, 7.66993463e-16]])
```

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

```
test_user = np.mat(user_item_matrix__test.values)
test_user.shape, test_user
```

```
((1, 10000), matrix([[0., 5., 5., ..., 0., 0., 0.]]))
```

```
tmp = test_user * Ur * np.linalg.inv(Sr)
tmp
```

```
matrix([[0.19423073, 0.04758859, 0.1318399 ]])
```

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

```
array([[ 0.47798051],
       [-0.15897535],
       [-0.2281112 ],
       [-0.08105948],
       [ 0.0397638 ],
       [-0.28908537],
       [-0.14303609],
       [-0.18656092],
       [-0.16023771],
       [-0.07543555]])
```

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

```
array([ 0.47798051, -0.15897535, -0.2281112 , -0.08105948,  0.0397638 ,
       -0.28908537, -0.14303609, -0.18656092, -0.16023771, -0.07543555])
```

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

```
438
```

```
book_list = list(user_item_matrix.columns)
def book_recommend(ind):
    try:
        book_id = book_list[ind]
        flt_rating = rating[rating['book_id'] == book_id]
        rating = flt_rating['book_id'].values[0]
        book_rating = df_book[df_book['book_id'] == rating]
        res = book_rating['original_title'].values[0]
        return res
    except:
        return ''
```

```python
i=1
for idx, item in enumerate(np.ndarray.flatten(np.array(test_user))):
    if item > 0:
        book_name = book_recommend(idx)
        print('{} - {}'.format(idx, item))
        if i==20:
            break
        else:
            i+=1
```

```
1 - 5.0
2 - 5.0
5 - 5.0
7 - 5.0
9 - 5.0
10 - 5.0
11 - 5.0
12 - 5.0
13 - 5.0
14 - 5.0
15 - 5.0
18 - 5.0
29 - 5.0
32 - 5.0
33 - 5.0
34 - 5.0
35 - 5.0
38 - 5.0
39 - 5.0
42 - 5.0
```

Книги, которые оценивал наиболее схожий пользователь:

```python
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:
        book_name = book_recommend(idx)
        print('{} - {}'.format(idx, item))
        if i==20:
            break
        else:
            i+=1
```

```
0 - 3.0
3 - 5.0
6 - 3.0
8 - 3.0
10 - 4.0
16 - 5.0
17 - 4.0
19 - 5.0
21 - 3.0
22 - 2.0
26 - 5.0
30 - 4.0
32 - 3.0
34 - 3.0
37 - 4.0
39 - 1.0
44 - 3.0
45 - 4.0
62 - 3.0
63 - 3.0
```

Список литературы

Источник набора данных:

https://www.kaggle.com/datasets/zygmunt/goodbooks-10k