INDENG 243 Project - Module 2

GoodReads: Book Analytics & Recommendation System

- @Group: 18

Agenda

- Model Data Preparation
- Recommendation models
  - Popularity Model (Baseline)
  - Content-based Filtering
  - Collaborative Filtering
  - Hybrid Model
- NLP Model
  - Tag filtering system
  - Extractive summarization
- Summay & Future plans

Part 1) Model data preparation

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

df_original = pd.read_csv('./Datasets/Book_info_original.csv')
```

1.1 Data Revise

In previous exploratory data analysis, we observed some potential flaws in original datasets:

1.1 Insufficient *manga* books

- Books under genre ***manga*** seems being especially insufficient in data (only 20 books) compared to other genres (100~300 books)

In [10]:
```python
len(df_original[df_original['Genre'] == 'manga'])
```

Out[10]:
```
20
```

1.2 Hidden duplicated books

- Interestingly, some books are implicitly duplicated in original data: they only differ in `Genre` but all these records refer to a same book;
- The resaon is that in our previous web scraping, for simplicity we keep the pre-defined 40 genres as the main `Genre` attribute for each book, but sometimes a single book will be listed under many different genres, resulting in *'duplicated'* records.
  - E.g. See the following *Harry Potter and the Chamber of Secrests*, it actually was listed under fantasy, fiction, children, etc
- However, these implicit duplicates are not detected by codes directly using ***.duplicated()***

In [12]:
```python
# if directly using .duplicated() to detect duplicates
df_original.duplicated().sum()
```

Out[12]:
```
0
```

In [15]:
```python
df_original[df_original['Uid'] == 15881].head(4)
```

Out[15]:

	Uid	Title	Author	Genre	Sub_Genres	Rating	Publish_Date	Page_Num	Award	Description	Author_Desc	Book_Aut
974	15881	Harry Potter and the Chamber of Secrets	J.K. Rowling	children-s	['Fiction', 'Young Adult', 'Magic', 'Childrens...	4.43	July 2, 1998	341	['Mythopoeic Fantasy Award', 'British Book Awa...	Ever since Harry Potter had come home for the ...	See also: Robert GalbraithAlthough she writes ...	
2509	15881	Harry Potter and the Chamber of Secrets	J.K. Rowling	ebooks	['Fiction', 'Young Adult', 'Magic', 'Childrens...	4.43	July 2, 1998	341	['Mythopoeic Fantasy Award', 'British Book Awa...	Ever since Harry Potter had come home for the ...	See also: Robert GalbraithAlthough she writes ...	
2671	15881	Harry Potter and the Chamber of Secrets	J.K. Rowling	fantasy	['Fiction', 'Young Adult', 'Magic', 'Childrens...	4.43	July 2, 1998	341	['Mythopoeic Fantasy Award', 'British Book Awa...	Ever since Harry Potter had come home for the ...	See also: Robert GalbraithAlthough she writes ...	
2869	15881	Harry Potter and the Chamber of Secrets	J.K. Rowling	fiction	['Fiction', 'Young Adult', 'Magic', 'Childrens...	4.43	July 2, 1998	341	['Mythopoeic Fantasy Award', 'British Book Awa...	Ever since Harry Potter had come home for the ...	See also: Robert GalbraithAlthough she writes ...	

Subsequently this observatin gives a rise to other fundamental problems:

- 1) ***Which of these duplicated records should we keep?*** (i.e. Which genre you think these books should be?)
  - It is hard to answer because a book's content might interact with many different genres and randomly keeping one record is unreasonable;
  - So we decided to obtain each book's genre list by re-scrape it under book's information page, rather than genre classification given by website
- 2) If we drop the duplicates, the number of unique books are greatly reduced (8032 --> 5545)

In [116...
```python
print("The original total book number is: ", len(df_original))
print("The unique book number is: ", len(df_original.drop_duplicates(subset=['Uid', 'Title'])))
```

```
The original total book number is:  8032
The unique book number is:  5545
```

1.3 Biased reviews

- Review dataset might be biased: more positive reviews than negative ones (feedback from Module 1)
- Currently # **Negative** review (Rating: 1~3) : # **Positive** review (Rating: 4~5) = **1 : 4** (roughly), unbalanced

To solve the above problems, we decide to re-scrape additional book data, which is in nature the best and straightforward solution

The revised dataset has the following improvements targeting previous probems:

- More *manga* books: 20 --> 140
- Re-scrape the book genre list: see detailed code in `Uid_Genre.py`
- Re-scrape more unique books, 5545 --> 7846 (`Genre_Book_Add.py`)
- Correspondingly more book reviews: 80461 --> 115033 and we purposely select more negative reviews to make dataset more balanced
  - # **Negative** review (Rating: 1~3) : # **Positive** review (Rating: 4~5) = **1 : 2** (more balanced compared to before)

For data combination, cleansing and some pre-processing steps, since they are lengthy and not close to this module's topic, you can see detailed codes in Data_Revise_Cleansing.ipynb if you like. We will directly use the further cleaned datasets in following sections:

- **Book_info_cleaned.csv**
- **Book_reviews_cleaned.csv**
- **Book_stats** (folder for all book statistics, since 1 book has 4 x 170 entries, we keep them separately)

1.2 Datasets modification for model use

1.2.1 Book information dataset: `df_info` dataframe

In [16]:
```python
df_info = pd.read_csv('./Datasets/Basic_datasets/Book_info_cleaned.csv')
```

In [17]:
```python
df_info.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7776 entries, 0 to 7775
Data columns (total 19 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Uid            7776 non-null   int64
 1   Title          7776 non-null   object
 2   Genres         7776 non-null   object
 3   Author         7776 non-null   object
 4   Rating         7776 non-null   float64
 5   Publish_Date   7776 non-null   object
 6   Page_Num       7776 non-null   int64
 7   Award          7776 non-null   object
 8   Description    7761 non-null   object
 9   Author_Desc    7116 non-null   object
 10  Book_Authored  7776 non-null   int64
 11  Follower_Num   7776 non-null   int64
 12  Review_Num     7776 non-null   int64
 13  Rating_Num     7776 non-null   int64
 14  Five_Star      7776 non-null   int64
 15  Four_Star      7776 non-null   int64
 16  Three_Star     7776 non-null   int64
 17  Two_Star       7776 non-null   int64
 18  One_Star       7776 non-null   int64
dtypes: float64(1), int64(11), object(7)
memory usage: 1.1+ MB
```

Turn rating distribution into percentage

- Since different books have different volume of ratings number, it is more reasonable to look at the percentage of each rating category rather than the real rating number. So we first compute the rating percentages as follows:

In [18]:
```python
df_info['Five_star_percent'] =  df_info['Five_Star'] / df_info['Rating_Num']
df_info['Four_star_percent'] =  df_info['Four_Star'] / df_info['Rating_Num']
df_info['Three_star_percent'] =  df_info['Three_Star'] / df_info['Rating_Num']
df_info['Two_star_percent'] =  df_info['Two_Star'] / df_info['Rating_Num']
df_info['One_star_percent'] =  df_info['One_Star'] / df_info['Rating_Num']
```

In [110...
```python
df_info = df_info.drop(['Five_Star', 'Four_Star', 'Three_Star', 'Two_Star', 'One_Star'], axis=1)
```

Data pre-processing before using `df_info` dataframe

- Because the list-type data are stored as *strings*, we need to turn them back to the correct data type.

In [20]:
```python
from ast import literal_eval

df_info['Genres'] = df_info['Genres'].apply(lambda x: literal_eval(x) if "[" in x else x)
df_info['Award'] = df_info['Award'].apply(lambda x: literal_eval(x) if "[" in x else x)
```

Award - Ordinal Encoding

- We use the number of awards the book has obtained to represent the 'Award' attribute
- https://analyticsindiamag.com/a-complete-guide-to-categorical-data-encoding/

In [21]:
```python
Award_Num = df_info['Award'].apply(lambda x: 0 if x == ['no'] else len(x))
df_info['Award_Num'] = Award_Num
```

We look at the book ratings' distribution

In [48]:
```python
print("The number of low rating books (Rating <= 4.0): ", len(df_info[df_info['Rating'] < 4.0]))
print("The number of high rating books (Rating > 4.0): ", len(df_info[df_info['Rating'] >= 4.0]))
```

```
The number of low rating books (Rating <= 4.0):  2992
The number of high rating books (Rating > 4.0):  4784
```

Book Statistics

The book statistics data reflects the ***changes*** (compared to previous day) in the following attributes over past 6 months:

- **date**: The date for these statistics
- **added**: changes of times this book has been added to users' bookshelves from previous day
- **ratings**: changes of times this book has been rated by users from previous day
- **reveiws**: changes of times this book is left reviews by users from previous day
- **to-read**: changes of times this book has been marked as 'to-read' by users

(*Note: the first row in file is the sum of these statistics until the day we scraped the data*)

We want to combine book statistics into its information dataframe `df_info`, however, each book only has one entry in information dataframe, while it has 4 x 170 records for its statistics. Directly combining them will make the dimensionality messy and hard to interpret, so we decide to use their statistical indicators for better measurement:

- **Median**: measures the central tendency of data distribution
- **IQR** (Interquatile Range): measures the dispersion level of data distributiion (*more robust to scale problem compared to variance*)
  - https://en.wikipedia.org/wiki/Robust_measures_of_scale

In [36]:
```python
import os

path = './Partial_datasets/Book_stats/'
filenames = os.listdir(path)
```

In [60]:
```python
df_demo = pd.read_csv(path + filenames[0])
df_demo.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 172 entries, 0 to 171
Data columns (total 5 columns):
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0   date     172 non-null    object
 1   added    172 non-null    int64
 2   ratings  172 non-null    int64
 3   reviews  172 non-null    int64
 4   to-read  172 non-null    int64
dtypes: int64(4), object(1)
memory usage: 6.8+ KB
```

Combine book statistics and compute statistical indicators simultaneously

In [38]:
```python
df_info_stats = pd.DataFrame()

for file in filenames:
    uid = int(file.split('_stats')[0])
    stats_df = pd.read_csv(path + file)

    # the first line is the sum of all following statistics, so separately processing it
    data = stats_df.iloc[0, [1, 4]].astype('int64').values
    data_df = pd.DataFrame(data = [uid] + list(data), index = ['Uid', 'AddedShelf', 'ToRead'])

    # compute median & IQR
    stats = stats_df.iloc[1:, 1:]
    IQR_df = (stats.quantile(q=0.75) - stats.quantile(q=0.25)).add_suffix('_IQR')
    median_df = stats.median().add_suffix('_median')

    stats_combine = pd.concat([data_df, median_df, IQR_df]).T
    df_info_stats = pd.concat([df_info_stats, stats_combine], ignore_index=True)
```

In [39]:
```python
df_info_stats[['Uid', 'AddedShelf', 'ToRead']] = df_info_stats[['Uid', 'AddedShelf', 'ToRead']].astype('int64')
df_info_stats
```

Out[39]:

	Uid	AddedShelf	ToRead	added_median	ratings_median	reviews_median	to-read_median	added_IQR	ratings_IQR	reviews_IQR	rea
0	100021	13107	6471	7.0	2.0	0.0	4.0	3.00	2.00	0.0	
1	10006486	2627	1703	1.0	0.0	0.0	1.0	1.00	0.00	0.0	
2	1000751	124063	26433	24.0	7.0	1.0	7.0	8.00	7.00	1.0	
3	10008056	36918	6637	12.0	4.0	0.0	2.0	6.00	4.75	0.0	
4	10009377	27195	11902	22.0	6.0	0.0	9.0	17.75	5.00	1.0	
...	...	...	...	...	...	...	...	...	...	...	
7771	99713	22569	8889	3.0	1.0	0.0	2.0	3.00	1.00	0.0	
7772	998	244540	121383	101.0	28.0	1.0	59.0	39.00	12.00	2.0	
7773	99944	192255	98182	58.0	10.0	1.0	35.0	18.00	7.00	1.0	
7774	99955	35739	18080	5.0	1.0	0.0	3.0	2.50	1.00	0.0	
7775	9999107	85198	32656	19.0	5.0	0.0	7.0	7.75	5.00	1.0	

7776 rows × 11 columns

Combine statistics data with origianl `df_info` dataframe

In [41]:
```python
df_info = df_info.merge(df_info_stats, on='Uid')
```

In [42]:
```python
# Store as csv for further use
df_info.to_csv('./Datasets/Basic_datasets/Book_info_model.csv', index=False)
```

1.2.2 Book reviews dataset: `df_reviews` dataframe

In [117...
```python
df_reviews = pd.read_csv('./Datasets/Basic_datasets/Book_reviews_cleaned.csv')
df_reviews.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 114034 entries, 0 to 114033
Data columns (total 10 columns):
 #   Column         Non-Null Count   Dtype
---  ------         --------------   -----
 0   Uid            114034 non-null  int64
 1   Title          114034 non-null  object
 2   Reviewer       114034 non-null  object
 3   N_Review       114034 non-null  int64
 4   N_Follower     114034 non-null  int64
 5   Review_Rating  114034 non-null  int64
 6   Review_Date    114034 non-null  object
 7   Content        114034 non-null  object
 8   N_Likes        114034 non-null  int64
 9   N_Comments     114034 non-null  int64
dtypes: int64(6), object(4)
memory usage: 8.7+ MB
```

Generally we keep the same ratio of negative : positive ratings as book information datasets (around 1 : 2)

In [118...
```python
print("The number of negative reviews (Rating: 1~3): ", len(df_reviews[df_reviews['Review_Rating'] < 4]))
print("The number of positive reviews (Rating: 4~5): ", len(df_reviews[df_reviews['Review_Rating'] >= 4]))
```

```
The number of negative reviews (Rating: 1~3):  35203
The number of positive reviews (Rating: 4~5):  78831
```

We want to examine our ***unique*** users for the use in further recommendation models

- Here ***unique*** means these users not only share the same name but also the same number of reviews (`Reviewer` + `N_Review`)
- Because GoodReads allow users to use the same username to register an account, we would like to use the `N_Review` (# of reviews written to help identification)

In [119...
```python
df_reviews.groupby(by=['Reviewer', 'N_Review']).count()
```

Out[119]:

Reviewer	N_Review	Uid	Title	N_Follower	Review_Rating	Review_Date	Content	N_Likes	N_Comments
✿Amanda✿	**31**	1	1	1	1	1	1	1	1
Luna	**265**	4	4	4	4	4	4	4	4
(shan) Littlebookcove	**152**	1	1	1	1	1	1	1	1
- The Polybrary -	**313**	1	1	1	1	1	1	1	1
A.	**1163**	11	11	11	11	11	11	11	11
...	**...**	...	...	...	...	...	...	...	...
검스마	**165**	1	1	1	1	1	1	1	1
여리고	**71**	1	1	1	1	1	1	1	1
D r e y	**167**	6	6	6	6	6	6	6	6
F r a n k h	**845**	17	17	17	17	17	17	17	17
e l l i e	**152**	1	1	1	1	1	1	1	1

41271 rows × 8 columns

But the above result of unique users is actually inaccurate, please see the following example:

- These two users with the same name 'Luna' but different number of reviews are actually the **same** user (we checked on website)
- But why we see this situation happens? The reasons are the following:
  - 1) GoodReads website has some historical problem about user information updates, i.e. the user might have more reivew numbers than some historical timestamps, but the website did not update these information cascade;
  - 2) Our web scraping takes some time, the user's review number might have changed in this time interval, making them *different*.

P.S. You might notice that they have different `N_Follower` numbers, that is caused by web scraping error, we will solve it in the following part

In [121...
```python
df_reviews[df_reviews['Reviewer'] == 'Luna']
```

Out[121]:

	Uid	Title	Reviewer	N_Review	N_Follower	Review_Rating	Review_Date	Content	N_Likes	N_Comments
36645	47944	Empress of the World	Luna	638	43	4	August 21, 2011	There's not one thing that makes this book goo...	3	2
110764	112118	This Cold Heaven Seven Seasons in Greenland	Luna	645	4	4	April 6, 2011	Oh, Greenland. Someday I will get there and sa...	5	0

First we modify the user names for better matching

- Some reviewers actually are the same person, but the empty space inside the names make them *different* in code level:
  - e.g. 'Luna' and '   Luna'
- But we should also consider cases **if these users are actually not the same person, how can we distinguish them?** We will discuss this problem shortly after this. We first just modify the reviewer names for better format.
  - Actually the following user with name 'Luna' is an example, the 1st and 5th are the same user, while the other 4 are a different user

In [128...
```python
for index, row in df_reviews.iloc[[36645, 59944, 60198, 60782, 110764, 110967], 2].iteritems():
    print((index, row))
```

```
(36645, 'Luna')
(59944, '   Luna ')
(60198, '   Luna ')
(60782, '   Luna ')
(110764, 'Luna')
(110967, '   Luna ')
```

In [129...
```python
df_reviews.iloc[[36645, 59944, 60198, 60782, 110764, 110967], :]
```

Out[129]:

	Uid	Title	Reviewer	N_Review	N_Follower	Review_Rating	Review_Date	Content	N_Likes	N_Comments
36645	47944	Empress of the World	Luna	638	43	4	August 21, 2011	There's not one thing that makes this book goo...	3	2
59944	203310	Poetry Language Thought	Luna	265	16	4	September 22, 2014	This was a refreshing read. What I really like...	2	0
60198	232743	The Archaeology of Knowledge and The Discourse...	Luna	265	16	2	November 27, 2016	This is the sort of book that you feel that i...	4	0
60782	252648	The Postmodern Condition A Report on Knowledge	Luna	265	16	5	February 14, 2016	Postmodernism, What now? After the fall of the...	2	0
110764	112118	This Cold Heaven Seven Seasons in Greenland	Luna	645	4	4	April 6, 2011	Oh, Greenland. Someday I will get there and sa...	5	0
110967	1171160	Three Dialogues Between Hylas and Philonous	Luna	265	1	5	September 16, 2021	Basically the material world does not exist pe...	1	0

In [130...
```python
from string import punctuation

def remove_punctuation(document):
    document = document.replace(' ', '') # remove empty space
    no_punct = ''.join([character for character in document if character not in punctuation])

    if no_punct == '':
        return document
    else:
        return no_punct
```

In [131...
```python
df_reviews['Reviewer'] = df_reviews['Reviewer'].apply(remove_punctuation)
```

In [132...
```python
# reviewer names
names = df_reviews['Reviewer'].unique()
print(len(names))
```

```
23347
```

The number of 'unique' (name + review number) users are not much changed from before

- To some extent, we would say our operation of modifying name format did not make too much negative impacts on data integrity

In [133...
```python
print("The number of unique users are: ", len(df_reviews.groupby(by=['Reviewer', 'N_Review']).count()))
```

```
The number of unique users are:  41255
```

To tackle this problem, our approach is to combine reviewers' entries with the same name & *close* review numbers

- We **assume that the user with the same name and close number of reviews are the same user.**
- From deep observation and several trials on original data, we set 100 as the limit for the definition of *close* reviews (i.e. absolute difference is smaller or euqal to 100), and we will check the quality of this operation afterwards.

In [382...
```python
# we use the copy to avoid directly operating on original data
df_reviews_copy = df_reviews.copy()
```

In [ ]:
```python
for name in names:
    i = 1
    temp_group = []
    temp_non_group = []
    review_group = [0]
    non_review_group = [0]

    flag = False
    while (temp_group != review_group) & (temp_non_group != non_review_group):
        print("Current user name: %s, Round: %d" % (name, i))
        temp_group = review_group[:]
        temp_non_group = non_review_group[:]

        if flag:
            break

        same_name_entries = df_reviews_copy[df_reviews_copy['Reviewer'] == name]
        if len(same_name_entries) > 1:
            temp = same_name_entries.groupby(by=['N_Review']).count()['Uid']
            if len(temp) == 1:
                flag = True
                continue

            # find more than one entry user's review number
            if i == 1:
                review_group = list(temp[temp > 1].index.values)
                non_review_group = list(temp[temp == 1].index.values)
            else:
                review_group = temp_group[:]
                non_review_group = temp_non_group[:]

            # if exists aggregated entries
            remove_group = []
            remove_non_group = []

            if review_group:
                # group v.s. group
                if len(review_group) >= 2:
                    for review_num_1 in review_group:
                        for review_num_2 in review_group:
                            if review_num_1 == review_num_2:
                                continue

                            if np.abs(review_num_1 - review_num_2) <= 100:
                                same_name_entries = df_reviews_copy[df_reviews_copy['Reviewer'] == name]
                                if review_num_1 < review_num_2:
                                    index = list(same_name_entries[same_name_entries['N_Review'] == \
                                                                   review_num_1].index.values)
                                    df_reviews_copy.loc[index, 'N_Review'] = review_num_2
                                    remove_group.append(review_num_1)

                                else:
                                    index = list(same_name_entries[same_name_entries['N_Review'] == \
                                                                   review_num_2].index.values)
                                    df_reviews_copy.loc[index, 'N_Review'] = review_num_1
                                    remove_group.append(review_num_2)

#                print('-------------------------------------------------------')
                review_group = [i for i in review_group if i not in set(remove_group)]
#                print(review_group)
#                print(non_review_group)

                # group v.s. independent sample
                for review_num in review_group:
                    for non_group in non_review_group:
                        if np.abs(review_num - non_group) <= 100:
                            same_name_entries = df_reviews_copy[df_reviews_copy['Reviewer'] == name]
                            if review_num > non_group:
                                index = list(same_name_entries[same_name_entries['N_Review'] == \
                                                               non_group].index.values)
                                df_reviews_copy.loc[index, 'N_Review'] = review_num  # change values
                                remove_non_group.append(non_group)  # drop already allocated ones
                            else:
                                index = list(same_name_entries[same_name_entries['N_Review'] == \
                                                               review_num].index.values)
                                df_reviews_copy.loc[index, 'N_Review'] = non_group  # change values
                                remove_group.append(review_num)

#            print('------------------------------------------------------------')
            non_review_group = [i for i in non_review_group if i not in set(remove_non_group)]
            review_group = [i for i in review_group if i not in set(remove_group)]
#            print(review_group)
#            print(non_review_group)

            # independent sample v.s. independent sample
            if not non_review_group:
                flag = True
                continue
            else:
                for non_group_1 in non_review_group:
                    for non_group_2 in non_review_group:
                        if non_group_1 == non_group_2:
                            continue

                        if np.abs(non_group_1 - non_group_2) <= 50:
                            same_name_entries = df_reviews_copy[df_reviews_copy['Reviewer'] == name]
                            if non_group_1 < non_group_2:
                                index = list(same_name_entries[same_name_entries['N_Review'] == \
                                                               non_group_1].index.values)
                                df_reviews_copy.loc[index, 'N_Review'] = non_group_2
                                remove_non_group.append(non_group_1)
                            else:
                                index = list(same_name_entries[same_name_entries['N_Review'] == \
                                                               non_group_2].index.values)
                                df_reviews_copy.loc[index, 'N_Review'] = non_group_1
                                remove_non_group.append(non_group_2)

#            print('------------------------------------------------------------')
            non_review_group = [i for i in non_review_group if i not in set(remove_non_group)]
#            print(review_group)
#            print(non_review_group)


            i += 1
```

41255 'unique' users --> 27581 unique users (much reduced)

In [135...
```python
print("The number of unique users after combination are: ", len(df_reviews_copy.groupby(by=['Reviewer', 'N_Revi
```

```
The number of unique users after combination are:  27581
```

Solve the error caused in web scraping

- Minor mistake in regular expressions causes the `N_Follower` data is wrong: only matched the first digit
- We use the previous combination result, taking the highest `N_Follower` number of the same user to replace all entries

In [29]:
```python
for name in names:
    same_name_entries = df_reviews_copy[df_reviews_copy['Reviewer'] == name]

    # only operate on usernames with more than 1 entries
    if len(same_name_entries) > 1:
            temp = same_name_entries.groupby(by=['N_Review']).count()['Uid']

            # if they already all shares the same N_Review, jump to next one
            if len(temp) == len(same_name_entries):
                continue

            review_group = list(temp[temp > 1].index.values)
            for review_num in review_group:
                same_review_df = same_name_entries[same_name_entries['N_Review'] == review_num]
                # find the maximum N_follower as the most updated data to replace all other for same user
                max_follower_num = [same_review_df['N_Follower'].max()]

                index = list(same_name_entries[same_name_entries['N_Review'] == review_num].index.values)
                dup_follower_num = [i for i in max_follower_num for _ in range(len(index))] # duplicate for len
                df_reviews_copy.loc[index, 'N_Follower'] = dup_follower_num
```

Assign a unique `UserID` for each different user to better distinguish them

In [222...
```python
df_reviews_copy.loc[:, 'UserID'] = df_reviews_copy.groupby(['Reviewer', 'N_Review']).ngroup()
```

In [ ]:
```python
# adjust the column display
cols = df_reviews_copy.columns.to_list()

cols = cols[0:2] + cols[-1:] + cols[2:3] + cols[5:6] + cols[3:5] + cols[6:-1]
df_reviews_copy = df_reviews_copy[cols]
```

We can see that 3 different users with the same name 'Luna' has been identified and the wrong `N_Follower` has been modified

In [136...
```python
df_reviews_copy[df_reviews_copy['Reviewer'] == 'Luna']
```

Out[136]:

	Uid	Title	UserID	Reviewer	Review_Rating	N_Review	N_Follower	Review_Date	Content	N_Likes	N_Comments
32810	465226	The Redbreast	15570	Luna	5	126	23	October 28, 2022	INCREDIBLE. Really just a work of art! You kn...	34	18
36645	47944	Empress of the World	15572	Luna	4	645	43	August 21, 2011	There's not one thing that makes this book goo...	3	2
59944	203310	Poetry Language Thought	15571	Luna	4	265	16	September 22, 2014	This was a refreshing read. What I really like...	2	0
60198	232743	The Archaeology of Knowledge and The Discourse...	15571	Luna	2	265	16	November 27, 2016	This is the sort of book that you feel that i...	4	0
60782	252648	The Postmodern Condition A Report on Knowledge	15571	Luna	5	265	16	February 14, 2016	Postmodernism, What now? After the fall of the...	2	0
110752	112118	This Cold Heaven Seven Seasons in Greenland	15572	Luna	4	645	43	April 6, 2011	Oh, Greenland. Someday I will get there and sa...	5	0
110955	1171160	Three Dialogues Between Hylas and Philonous	15571	Luna	5	265	16	September 16, 2021	Basically the material world does not exist pe...	1	0

But one potential flaw of this approach is that: we might introduce one extra review of a 'same' user for the same book

- We checked this problem, the maximum number of same-named reviewers under the same book is 2, and we drop one of these entries

In [231...
```python
same_book_reviewer = df_reviews_copy.groupby(by=['Uid', 'UserID']).count().sort_values(by=['Title'])
same_book_reviewer[same_book_reviewer['Title'] > 1]
```

Out[231]:

Uid	UserID	Title	Reviewer	Review_Rating	N_Review	N_Follower	Review_Date	Content	N_Likes	N_Comments
40604846	**4246**	2	2	2	2	2	2	2	2	2
53138099	**12977**	2	2	2	2	2	2	2	2	2
31463	**1860**	2	2	2	2	2	2	2	2	2
57693474	**12977**	2	2	2	2	2	2	2	2	2
30241	**21737**	2	2	2	2	2	2	2	2	2
153540	**4246**	2	2	2	2	2	2	2	2	2
18104725	**4246**	2	2	2	2	2	2	2	2	2

In [238...
```python
df_reviews_copy.drop_duplicates(subset=['Uid', 'UserID'], inplace=True)
```

In [239...
```python
df_reviews_copy.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 114013 entries, 0 to 114019
Data columns (total 11 columns):
 #   Column         Non-Null Count   Dtype
---  ------         --------------   -----
 0   Uid            114013 non-null  int64
 1   Title          114013 non-null  object
 2   UserID         114013 non-null  int64
 3   Reviewer       114013 non-null  object
 4   Review_Rating  114013 non-null  int64
 5   N_Review       114013 non-null  int64
 6   N_Follower     114013 non-null  int64
 7   Review_Date    114013 non-null  object
 8   Content        114013 non-null  object
 9   N_Likes        114013 non-null  int64
 10  N_Comments     114013 non-null  int64
dtypes: int64(7), object(4)
memory usage: 10.4+ MB
```

In [240...
```python
# store modified reviews dataset

df_reviews_copy.to_csv('./Datasets/Basic_datasets/Book_reviews_modified.csv', index=False)
```

1.2.3 Mitigate the sparsity of recommendation matrix

The above modification process is time-consuming, you can simply start from reading our modified files for following operations

In [241...
```python
df_reviews_copy = pd.read_csv('./Datasets/Basic_datasets/Book_reviews_modified.csv')
```

We look at how many reviews each user has left for books in our dataset

- Most users actually only left 1 review, making our dataset super sparse: we need to estimate almost 99.5% of ratings

In [242...
```python
reviewer_book_count = df_reviews_copy.groupby(by=['UserID']).count()
reviewer_book_count.sort_values(['Uid'], ascending=False)
```

Out[242]:

UserID	Uid	Title	Reviewer	Review_Rating	N_Review	N_Follower	Review_Date	Content	N_Likes	N_Comments
15602	380	380	380	380	380	380	380	380	380	380
17161	350	350	350	350	350	350	350	350	350	350
2557	347	347	347	347	347	347	347	347	347	347
7740	318	318	318	318	318	318	318	318	318	318
1863	315	315	315	315	315	315	315	315	315	315
...	...	...	...	...	...	...	...	...	...	...
11248	1	1	1	1	1	1	1	1	1	1
11246	1	1	1	1	1	1	1	1	1	1
11245	1	1	1	1	1	1	1	1	1	1
11244	1	1	1	1	1	1	1	1	1	1
27580	1	1	1	1	1	1	1	1	1	1

27581 rows × 10 columns

In [245...
```python
print("The user number is: ", len(reviewer_book_count))
print("The number of books is: ", len(df_info))
print(" ")
print("The total ratings needed are: ", len(reviewer_book_count) * len(df_info))
print("The known records are: ", len(df_reviews_copy))
print("The rating entries need to be estimated are: ", \
      len(reviewer_book_count) * len(df_info) - len(df_reviews_copy))
print('')

ratio = len(df_reviews_copy) / (len(reviewer_book_count) * len(df_info))
print("The ratio of known data is: %.2f" % (ratio * 100) + '%')
```

```
The user number is:  27581
The number of books is:  7776

The total ratings needed are:  214469856
The known records are:  114013
The rating entries need to be estimated are:  214355843

The ratio of known data is: 0.05%
```

Currently our dataset will be too sparse, so we consider to make it more compat from two directions:

- 1) Drop some books without enough reviews
- 2) Set an interaction threshold to select users more actively rate and review books

1) Drop books without enough reviews

In [246...
```python
book_review_count = df_reviews_copy.groupby(by = ['Uid']).count()
```

In [247...
```python
# drop books without enough reviews
uid_remove = book_review_count[book_review_count['UserID'] < 10].index.values
print("The number of books left are: ", len(df_info) - len(uid_remove))

# use a copy to keep original dataframe for repeated experiments
df_reviews_modified = df_reviews_copy.copy()
df_reviews_modified = df_reviews_modified[~df_reviews_modified['Uid'].isin(uid_remove)]

print("The number of review records left are: ", len(df_reviews_modified))
```

```
The number of books left are:  7627
The number of review records left are:  113025
```

2) Set a threshold to select more active users, we visualize this process to find some *balanced* points

- *balanced*: less sparse, but keep as much books as possible

In [248…]:

```python
threshold_list = np.linspace(0, 120, 121, dtype='int64')

ratio = []
book_num = []
record_num = []

for threshold in threshold_list:
    reviewer_id = reviewer_book_count[reviewer_book_count['Uid'] >= threshold].index.get_level_values('UserID')
    reviewer_df = df_reviews_modified[(df_reviews_modified['UserID'].isin(reviewer_id))]

    total = len(reviewer_id) * len(reviewer_df['Uid'].unique())   # total ratings needed
    records = len(reviewer_df)

    book_num.append(len(reviewer_df['Uid'].unique()))
    record_num.append(records)
    ratio.append(records / total)
```

In [249…]:

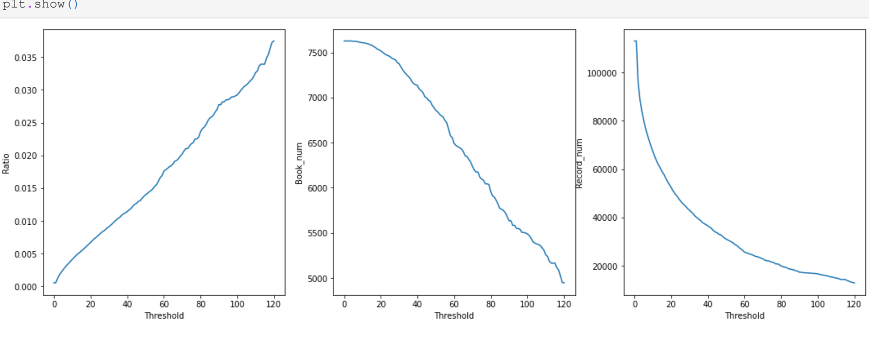
```python
import matplotlib.pyplot as plt

plt.figure(figsize=(18, 6))
plt.subplot(1, 3, 1)
plt.plot(threshold_list, ratio)
plt.xlabel('Threshold')
plt.ylabel('Ratio')

plt.subplot(1, 3, 2)
plt.plot(threshold_list, book_num)
plt.xlabel('Threshold')
plt.ylabel('Book_num')

plt.subplot(1, 3, 3)
plt.plot(threshold_list, record_num)
plt.xlabel('Threshold')
plt.ylabel('Record_num')

plt.show()
```



Finally we choose the threshold as 40 (i.e. users with >= 40 reviews will be kept)

- Improve the sparsity to 1.14% known data (0.05% previously)

In [250…]:

```python
threshold = 40

reviewer_id = reviewer_book_count[reviewer_book_count['Uid'] >= threshold].index.get_level_values('UserID').to_
reviewer_df = df_reviews_modified[(df_reviews_modified['UserID'].isin(reviewer_id))]

total = len(reviewer_id) * len(reviewer_df['Uid'].unique())  # total ratings needed
print("The total reviewer number is: ", len(reviewer_id))
print("The total book number is: ", len(reviewer_df['Uid'].unique()))

records = len(reviewer_df)
print('')
print("The total number of ratings needed are: ", total)
print("The known records are: ", len(reviewer_df))
print("The rating entries need to be estimated are: ", total - len(reviewer_df))

ratio = records / total
print('')
print("The ratio of known data is: %.2f" % (ratio * 100) + '%')
```

```
The total reviewer number is:  449
The total book number is:  7133

The total number of ratings needed are:  3202717
The known records are:  36555
The rating entries need to be estimated are:  3166162

The ratio of known data is: 1.14%
```

In [251…]:

```python
# reset index
reviewer_df  = reviewer_df.reset_index(drop=True)

# store for recommendation models
reviewer_df.to_csv('./Datasets/Rec_models_datasets/User_interaction.csv', index=False)
```

Correspondingly we keep only those books are selected

In [252…]:

```python
df_info_model = pd.read_csv('./Datasets/Basic_datasets/Book_info_model.csv')
```

In [253…]:

```python
book_selected_uid = reviewer_df['Uid'].unique()
selected_book = df_info_model[df_info_model['Uid'].isin(book_selected_uid)].reset_index(drop=True)

# keep only the selected books
selected_book.to_csv('./Datasets/Rec_models_datasets/Selected_book_info.csv', index=False)
```

Part 2) Recommendation Models

Goal: Accurately recommend to users unread books that match their reading preferences.

- Tasks: our models will predict users' ratings for their unread books and then recommend (predicted) high-rating books to them.

In [99]:

```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import os
import math
import random

import warnings
warnings.filterwarnings("ignore")
```

Load book data & user reviews data

In [84]:

```python
books_selected = pd.read_csv('./Datasets/Rec_models_datasets/Selected_book_info.csv')
books_selected.head(5)
```

Out[84]:

	Uid	Title	Genres	Author	Rating	Publish_Date	Page_Num	Award	Description	Author_Desc	...
0	13642600	A Splash of Red The Life and Art of Horace Pippin	['picture-books', 'biography', 'art', 'nonfict...	Jen Bryant	3.87	January 8, 2013	34	['schneider_family_book_award', 'vermonts_pict...	As a child in the late 1800s, Horace Pippin lo...	Jen Bryant (Jennifer Fisher Bryant) writes pic...	...
1	137933	After the End of Art Contemporary Art and the ...	['art', 'philosophy', 'nonfiction', 'art-histo...	Arthur C. Danto	4.03	January 1, 1997	264	['no']	Over a decade ago, Arthur Danto announced that...	Arthur C. Danto was Johnsonian Professor Emeri...	...
2	52374	Against Interpretation and Other Essays	['essays', 'nonfiction', 'philosophy', 'art', ...	Susan Sontag	4.13	January 1, 1966	312	['national_book_award_finalist']	Against Interpretation was Susan Sontag's firs...	Susan Sontag was born in New York City on Janu...	...
3	140987	Air Guitar Essays on Art and Democracy	['art', 'nonfiction', 'essays', 'music', 'crit...	Dave Hickey	4.08	August 2, 1997	208	['no']	The 23 essays (or "love songs") that make up t...	David Hickey (born circa 1939) is an American ...	...
4	51245	Amphigorey Also	['art', 'humor', 'graphic-novels', 'comics', '...	Edward Gorey	4.40	January 1, 1983	256	['no']	Contents: The Utter Zoo, The Blue Aspic, The E...	Born in Chicago, Gorey came from a colourful f...	...

5 rows × 30 columns

In [114…]:

```python
from ast import literal_eval

# Turn 'list-like' string data into lists
books_selected['Genres'] = books_selected['Genres'].apply(lambda x: literal_eval(x) if "[" in x else x)
books_selected['Award'] = books_selected['Award'].apply(lambda x: literal_eval(x) if "[" in x else x)
```

In [10]:

```python
interactions_df = pd.read_csv('./Datasets/Rec_models_datasets/User_interaction.csv')
interactions_df.head(5)
```

Out[10]:

	Uid	Title	UserID	Reviewer	Review_Rating	N_Review	N_Follower	Review_Date	Content	N_Likes	N_Comments
0	13642600	A Splash of Red The Life and Art of Horace Pippin	192	Abigail	4	7086	173	February 20, 2021	Author Jen Bryant and illustrator Melissa Swee...	3	2
1	13642600	A Splash of Red The Life and Art of Horace Pippin	17464	Michelle	4	301	38	July 10, 2013	Audience: PrimaryGenre: Non-Fiction/Informatio...	3	0
2	137933	After the End of Art Contemporary Art and the ...	17298	Michael	5	718	969	November 14, 2007	As I recall, a great book despite my predilect...	1	1
3	137933	After the End of Art Contemporary Art and the ...	13002	Kate	5	396	316	January 7, 2008	Changed entirely how I think about art. It sta...	1	0
4	52374	Against Interpretation and Other Essays	17298	Michael	4	718	969	March 16, 2020	A wide-ranging debut collection of essays on a...	67	2

Train & test split

In [12]:

```python
from sklearn.model_selection import train_test_split

interactions_train_df, interactions_test_df = train_test_split(interactions_df,
                                   stratify=interactions_df['UserID'],
                                   test_size=0.20,
                                   random_state=42)

print('# interactions on Train set: %d' % len(interactions_train_df))
print('# interactions on Test set: %d' % len(interactions_test_df))
```

```
# interactions on Train set: 29249
# interactions on Test set: 7313
```

In [13]:

```python
# Indexing by 'UserID' to speed up the searches during evaluation

interactions_full_indexed_df = interactions_df.set_index('UserID')
interactions_train_indexed_df = interactions_train_df.set_index('UserID')
interactions_test_indexed_df = interactions_test_df.set_index('UserID')
```

Evaluation - Top-N accuracy metrics

We use the **Top-N accuracy metrics** to evaluate our recommendation models' performance:

- Accuracy of the top recommendations provided to a user, comparing to the items the user has actually interacted in test set

Pseudo code:

- For each user:
  - For each item the user has interacted in test set:
    - Sample 100 other items the user has **never interacted**;
    - Recommendation model produces a ranked list of items, from a set composed 1 interacted item and other 100 non-interacted items;
    - Compute the Top-N accuracy metrics for this user and interacted item from the recommendations ranked list
- Aggregate the ***global*** Top-N accuracy metrics

Here we use **Recall@N**: whether the interacted item is among the top N items (*hit*) in the ranked list of 101 recommendations for a user

- **Metrics**: Recall@5 and Recall@10
- E.g. Recall@5: For one user, if we have 100 randomly selected books, the percentage of the interacted books in the test set will be ranked among the top 5 books by the model

In [31]:

```python
# Get all bookIDs that the given user has interacted with

def get_items_interacted(person_id, interactions_df):

    interacted_items = interactions_df.loc[person_id]['Uid']  # interacted (books') Uids

    return set(interacted_items if type(interacted_items) == pd.Series else [interacted_items])
```

In [33]:

```python
# number of non-interacted items to be combined together for test
EVAL_RANDOM_SAMPLE_NON_INTERACTED_ITEMS = 100

class ModelEvaluator:

    def get_not_interacted_items_sample(self, person_id, sample_size, seed=42):
        interacted_items = get_items_interacted(person_id, interactions_full_indexed_df)
        all_items = set(books_selected['Uid'])
        non_interacted_items = all_items - interacted_items

        random.seed(seed)

        # Supress depreciation warning. random.sample will lose support for Sets,
        # should be convereted to a list or tuple instead
        with warnings.catch_warnings():
            warnings.filterwarnings("ignore")
            non_interacted_items_sample = random.sample(non_interacted_items, sample_size)

        return set(non_interacted_items_sample)

    def _verify_hit_top_n(self, item_id, recommended_items, topn):
            try:
                index = next(i for i, c in enumerate(recommended_items) if c == item_id)
            except:
                index = -1
            hit = int(index in range(0, topn))
            return hit, index

    def evaluate_model_for_user(self, model, person_id):
        # Getting the items in test set
        interacted_values_testset = interactions_test_indexed_df.loc[person_id]
        if type(interacted_values_testset['Uid']) == pd.Series:
            person_interacted_items_testset = set(interacted_values_testset['Uid'])
        else:
            person_interacted_items_testset = set([int(interacted_values_testset['Uid'])])
        interacted_items_count_testset = len(person_interacted_items_testset)

        # Getting a ranked recommendation list from a model for a given user
        person_recs_df = model.recommend_items(person_id,
                                               items_to_ignore=get_items_interacted(person_id, interactions_tra
                                               topn=10000000000)

        hits_at_5_count = 0
        hits_at_10_count = 0

        # For each item the user has interacted in test set
        for item_id in person_interacted_items_testset:
            # Getting a random sample (100) items the user has not interacted
            non_interacted_items_sample = self.get_not_interacted_items_sample(person_id,
                                                                              sample_size=EVAL_RANDOM_SAMPLE_NON_IN
                                                                              seed=item_id%(2**32))

            # Combining the current interacted item with the 100 random items
            items_to_filter_recs = non_interacted_items_sample.union(set([item_id]))

            # Filtering only recommendations that are either the interacted item
            # or from a random sample of 100 non-interacted items
            valid_recs_df = person_recs_df[person_recs_df['Uid'].isin(items_to_filter_recs)]
            valid_recs = valid_recs_df['Uid'].values

            # Verifying if the current interacted item is among the Top-N recommended items
            hit_at_5, index_at_5 = self._verify_hit_top_n(item_id, valid_recs, 5)
            hits_at_5_count += hit_at_5
            hit_at_10, index_at_10 = self._verify_hit_top_n(item_id, valid_recs, 10)
            hits_at_10_count += hit_at_10

        # Recall is the rate of the interacted items that are ranked among the Top-N recommended items
        recall_at_5 = hits_at_5_count / float(interacted_items_count_testset)
        recall_at_10 = hits_at_10_count / float(interacted_items_count_testset)

        person_metrics = {'hits@5_count':hits_at_5_count,
                          'hits@10_count':hits_at_10_count,
                          'interacted_count': interacted_items_count_testset,
                          'recall@5': recall_at_5,
                          'recall@10': recall_at_10}
        return person_metrics

    def evaluate_model(self, model):
        # print('Running evaluation for users')
        people_metrics = []
        for idx, person_id in enumerate(list(interactions_test_indexed_df.index.unique().values)):
            person_metrics = self.evaluate_model_for_user(model, person_id)
            person_metrics['_person_id'] = person_id

            people_metrics.append(person_metrics) # append into a complete list

        detailed_results_df = pd.DataFrame(people_metrics) \
                            .sort_values('interacted_count', ascending=False)

        # Global metrics for all users
        global_recall_at_5 = detailed_results_df['hits@5_count'].sum() / float(detailed_results_df['interacted_
        global_recall_at_10 = detailed_results_df['hits@10_count'].sum() / float(detailed_results_df['interacte

        global_metrics = {'modelName': model.get_model_name(),
                          'recall@5': global_recall_at_5,
                          'recall@10': global_recall_at_10}

        return global_metrics, detailed_results_df
```

In [34]:

```python
model_evaluator = ModelEvaluator()
```

2.1 Popularity Model (Baseline)

This model is not actually personalized - it simply recommends to a user ***the most popular items that the user has not previously consumed***.

- As the popularity accounts for the "wisdom of the crowds", it usually provides good recommendations, generally interesting for most people;

- But the main objective of a recommender system is to leverage the ***long-tail items*** to the users with very specific interests, which goes far beyond this simple technique. So we will use this model as a **baseline**.

In [35]:

```python
# Computes the most popular items
item_popularity_df = interactions_df.groupby('Uid')['Review_Rating'].sum().sort_values(ascending=False).reset_i
item_popularity_df.head(10)
```

Out[35]:

	Uid	Review_Rating
0	36576608	87
1	464260	73
2	11588	71
3	17899948	71
4	53799686	69
5	96358	69
6	18386	68
7	7126	68
8	5907	67
9	36373463	67

In [36]:

```python
class PopularityRecommender:

    MODEL_NAME = 'Popularity'

    def __init__(self, popularity_df, items_df=None):
        self.popularity_df = popularity_df
        self.items_df = items_df

    def get_model_name(self):
        return self.MODEL_NAME

    def recommend_items(self, user_id, items_to_ignore=[], topn=10, verbose=False):
        # Recommend the more popular items that the user hasn't seen yet.
        recommendations_df = self.popularity_df[~self.popularity_df['Uid'].isin(items_to_ignore)] \
                               .sort_values('Review_Rating', ascending = False) \
                               .head(topn)

        if verbose:
            if self.items_df is None:
                raise Exception('"items_df" is required in verbose mode')

            recommendations_df = recommendations_df.merge(self.items_df, how = 'left',
                                                          left_on = 'Uid', right_on = 'Uid')[['Review_Rating',

        return recommendations_df
```

Initialize an instance for Popularity model

In [37]:

```python
popularity_model = PopularityRecommender(item_popularity_df, books_selected)
```

In [38]:

```python
print('Evaluating Popularity recommendation model...')
pop_global_metrics, pop_detailed_results_df = model_evaluator.evaluate_model(popularity_model)

print('\nGlobal metrics:\n%s' % pop_global_metrics)
pop_detailed_results_df.head(10)
```

```
Evaluating Popularity recommendation model...
448 users processed

Global metrics:
{'modelName': 'Popularity', 'recall@5': 0.12457267879119377, 'recall@10': 0.2261725693969643}
```

Out[38]:

	hits@5_count	hits@10_count	interacted_count	recall@5	recall@10	_person_id
76	20	33	76	0.263158	0.434211	15602
40	14	26	70	0.200000	0.371429	17161
21	9	24	69	0.130435	0.347826	2557
7	10	20	63	0.158730	0.317460	1863
92	15	26	63	0.238095	0.412698	7740
45	12	22	62	0.193548	0.354839	26336
193	21	30	62	0.338710	0.483871	22026
57	14	16	61	0.229508	0.262295	421
287	21	31	60	0.350000	0.516667	16300
27	19	30	56	0.339286	0.535714	16765

2.2 Content-based Filtering

Content-based filtering approaches leverage description or attributes from items the user has interacted to recommend ***similar items***.

- It builds ***users' profiles (tastes)*** depending only on the user previous choices, making this method robust to avoid the *cold-start* problem.

Here we are using a very popular technique in information retrieval (search engines) named **TF-IDF**:

- This technique converts unstructured text into a vector structure, where each word is represented by a position in the vector, and the value measures ***how relevant a given word is for a book***;
- As all items will be represented in the same Vector Space Model, we will compute ***cosine similarity*** between books.

In [ ]:

```python
import scipy
from sklearn.preprocessing import MinMaxScaler, normalize
from sklearn.metrics.pairwise import cosine_similarity
```

Check NaN values in `Description`

In [87]:

```python
if books_selected['Description'].isnull().any():
    print("There is at least one NaN value in the 'Description' column.")
else:
    print("There are no NaN values in the 'Description' column.")
```

```
There is at least one NaN value in the 'Description' column.
```

To cover these missing book descriptions, we choose to use each book's `Title` + `Genres` + `Description` as its textual information `BookText` for constructing the words' vector space

In [115…]:

```python
for index, row in books_selected.iterrows():
    genre = ' '.join([str(i) for i in row['Genres']])

    book_desc = row['Description']
#     author_desc = row['Author_Desc']
    if isinstance(book_desc, float):
        text  = row['Title'] + genre
    else:
        text = row['Title'] + genre + book_desc

    # replace missing 'Description'
    books_selected.loc[index, 'BookText'] = text
```

Train word vectors based on book texts data

In [122…]:

```python
from nltk.corpus import stopwords
from sklearn.feature_extraction.text import TfidfVectorizer

# Stopwords (words with no semantics) from English
stopwords_list = stopwords.words('english') + ['book', 'books']

# Trains a model whose vectors size is 5000, composed by the main unigrams
# and bigrams found in the corpus, ignoring stopwords
vectorizer = TfidfVectorizer(analyzer='word',
                     ngram_range=(1, 2),
                     min_df=0.003,
                     max_df=0.5,
                     max_features=5000,
                     stop_words=stopwords_list)
```

In [123…]:

```python
# book Uids
item_ids = books_selected['Uid'].tolist()

# vectorize book description texts
tfidf_matrix = vectorizer.fit_transform(books_selected['BookText'])
tfidf_feature_names = vectorizer.get_feature_names()
tfidf_matrix
```

Out[123]:

```
<7133x5000 sparse matrix of type '<class 'numpy.float64'>'
	with 484277 stored elements in Compressed Sparse Row format>
```

Obtain the word vector representation of a book in the same feature space as the user profiles (i.e. TF-IDF matrix)

- Take all the book files the user has interacted with and average them weighted by user's `Review_Rating`

In [108…]:

```python
def get_item_profile(item_id):
    idx = item_ids.index(item_id)
    item_profile = tfidf_matrix[idx:idx+1]
    return item_profile

def get_item_profiles(ids):
    item_profiles_list = [get_item_profile(x) for x in ids]
    item_profiles = scipy.sparse.vstack(item_profiles_list)
    return item_profiles

def build_users_profile(person_id, interactions_indexed_df):
    interactions_person_df = interactions_indexed_df.loc[person_id]
    user_item_profiles = get_item_profiles(interactions_person_df['Uid'])

    user_item_strengths = np.array(interactions_person_df['Review_Rating']).reshape(-1,1)

    # Weighted average of item profiles by the interactions strength, and normalized
    user_item_strengths_weighted_avg = np.sum(user_item_profiles.multiply(user_item_strengths), axis=0) \
                                                                   / np.sum(user_item_strengths)
    user_profile_norm = normalize(user_item_strengths_weighted_avg)

    return user_profile_norm

def build_users_profiles():
    interactions_indexed_df = interactions_train_df[interactions_train_df['Uid'] \
                                                  .isin(books_selected['Uid'])].set_index('UserID')
    user_profiles = {}
    for person_id in interactions_indexed_df.index.unique():
        user_profiles[person_id] = build_users_profile(person_id, interactions_indexed_df)
    return user_profiles
```

In [220…]:

```python
user_profiles = build_users_profiles()
```

We take a look at a user profile example whose name is 'Abigail' (UserID = 192)

- The value in each position represents how relevant is a token (unigram or bigram) for the user named 'Abigail';
- It shows that she is very interested in reading books about ***children***:
  - Some keywords like ***bear, cat, little*** appear frequently in children's books.
  - Also note that ***Dr. Seuss*** is a famous writer for children's literatures

In [225…]:

```python
aprofile = user_profiles[192]

print(aprofile.shape)
pd.DataFrame(sorted(zip(tfidf_feature_names, user_profiles[192].flatten().tolist()), key=lambda x: -x[1])[:20],
             columns=['token', 'relevance'])
```

```
(1, 5000)
```

Out[225]:

	token	relevance
0	children	0.422296
1	dr seuss	0.169196
2	seuss	0.169196
3	children fiction	0.168590
4	animals	0.166772
5	picture	0.157434
6	bear	0.154855
7	fiction	0.145833
8	fiction classics	0.124478
9	dr	0.123242
10	classics	0.123204
11	cat	0.114586
12	little	0.114381
13	new	0.106283
14	hat	0.095753
15	young	0.094332
16	humor	0.094149
17	fiction animals	0.090396
18	picture fiction	0.089813
19	food	0.088952

In [102…]:

```python
class ContentBasedRecommender:

    MODEL_NAME = 'Content-Based'

    def __init__(self, items_df=None):
        self.item_ids = item_ids
        self.items_df = items_df

    def get_model_name(self):
        return self.MODEL_NAME

    def _get_similar_items_to_user_profile(self, person_id, topn=1000):
        # Computes the cosine similarity between the user profile and all item profiles
        cosine_similarities = cosine_similarity(user_profiles[person_id], tfidf_matrix)

        # Gets the top similar items & sort by similarity
        similar_indices = cosine_similarities.argsort().flatten()[-topn:]
        similar_items = sorted([(item_ids[i], cosine_similarities[0,i]) for i in similar_indices], key=lambda x

        return similar_items

    def recommend_items(self, user_id, items_to_ignore=[], topn=10, verbose=False):
        similar_items = self._get_similar_items_to_user_profile(user_id)
        #Ignores items the user has already interacted
        similar_items_filtered = list(filter(lambda x: x[0] not in items_to_ignore, similar_items))

        recommendations_df = pd.DataFrame(similar_items_filtered, columns=['Uid', 'Review_Rating']).head(topn)

        # If verbose is set to True, then the method returns a DataFrame that includes additional information
        # about the recommended items, such as their title, URL, and language.
        if verbose:
            if self.items_df is None:
                raise Exception('"items_df" is required in verbose mode')

            recommendations_df = recommendations_df.merge(self.items_df, how = 'left',
                                                          left_on = 'Uid',
                                                          right_on = 'Uid')[['Review_Rating', 'Uid', 'Title']]


        return recommendations_df
```

In [126…]:

```python
content_based_recommender_model = ContentBasedRecommender(books_selected)
```

In [127…]:

```python
print('Evaluating Content-Based Filtering model...')
cb_global_metrics, cb_detailed_results_df = model_evaluator.evaluate_model(content_based_recommender_model)

print('\nGlobal metrics:\n%s' % cb_global_metrics)
cb_detailed_results_df.head(10)
```

```
Evaluating Content-Based Filtering model...
448 users processed

Global metrics:
{'modelName': 'Content-Based', 'recall@5': 0.3638725557226856, 'recall@10': 0.4869410638588814}
```

Out[127]:

	hits@5_count	hits@10_count	interacted_count	recall@5	recall@10	_person_id
76	32	41	76	0.421053	0.539474	15602
40	21	34	70	0.300000	0.485714	17161
21	17	26	69	0.246377	0.376812	2557
7	33	36	63	0.523810	0.571429	1863
92	5	16	63	0.079365	0.253968	7740
45	19	26	62	0.306452	0.419355	26336
193	17	27	62	0.274194	0.435484	22026
57	7	14	61	0.114754	0.229508	421
287	36	40	60	0.600000	0.666667	16300
27	12	15	56	0.214286	0.267857	16765

Our content-based filtering model provides personalized recommendations with a **Recall@5 ≈ 0.3639**, indicating that around 36% of the items that the user interacted with in the test set were included in the top-5 recommended items generated by the model from a list of 100 random items. Furthermore, the **Recall@10 ≈ 0.4869**. This is a great improvement from baseline, partially proves the power of this technique.

2.3 Collaborative Filtering model

We use latent factor model (model-based) for collaborative filtering:

- Compress user-item matrix into a **low-dimensional** representation in terms of latent factors, solving sparsity problem;
- Here we a use popular latent factor model named Singular Value Decomposition (SVD).

Singular Value Decomposition:

$$M_{m\times n} = U_{m\times m} * \Sigma_{m\times n} * V_{n\times n}^T \ \ (Full\ SVD)$$

However, we can choose **the number of latent factors** k to factor the user-item matrix and *approximate* original matrix using the following formula:

$$M_{m\times n} \approx U_{m\times k} * \Sigma_{k\times k} * V_{k\times n}^T \ \ (Thin\ SVD)$$

- The higher the number of factors, the more precise is the factorization in the original matrix reconstructions.
- But if the model is allowed to memorize too much details of the original matrix, it may not generalize well for data it was not trained on. Reducing the number of factors increases the model generalization.
- We will loop over a potential space to find the **best** number of factors $k_{optimal}$

In [ ]:

```python
from scipy.sparse import csr_matrix
from scipy.sparse.linalg import svds
```

Matrix Factorization

In [141…]:

```python
# Creating a sparse pivot table with users in rows and items in columns
users_items_pivot_matrix_df = interactions_train_df.pivot(index='UserID',
                                                          columns='Uid',
                                                          values='Review_Rating').fillna(0)

users_items_pivot_matrix_df.head(10)
```

Out[141]:

Uid	1	2	5	6	11	13	21	22	24	25	...	61330005	61865476	62053325	62296528	62357989	62404966	62967897	632212
UserID																			
17	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
87	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
192	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
308	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
330	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
383	0.0	0.0	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	
421	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
486	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
523	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
612	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	

10 rows × 6907 columns

In [142…]:

```python
users_items_pivot_matrix = users_items_pivot_matrix_df.to_numpy()
users_items_pivot_matrix[:10]
```

Out[142]:

```
array([[0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       ...,
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.]])
```

In [143…]:

```python
users_ids = list(users_items_pivot_matrix_df.index)
users_ids[:10]
```

Out[143]:

```
[17, 87, 192, 308, 330, 383, 421, 486, 523, 612]
```

In [144…]:

```python
users_items_pivot_sparse_matrix = csr_matrix(users_items_pivot_matrix)
users_items_pivot_sparse_matrix
```

Out[144]:

```
<449x6907 sparse matrix of type '<class 'numpy.float64'>'
	with 29244 stored elements in Compressed Sparse Row format>
```

Here we first set number of factors $k = 40$, representing the number of book genres

In [226…]:

```python
# The number of factors to factor the user-item matrix (use the number of genres)
NUMBER_OF_FACTORS_MF = 40

# Performs matrix factorization of the original user item matrix
U, sigma, Vt = svds(users_items_pivot_sparse_matrix, k = NUMBER_OF_FACTORS_MF)
sigma = np.diag(sigma) # diagonize
```

In [227…]:

```python
U.shape, sigma.shape, Vt.shape
```

Out[227]:

```
((449, 40), (40, 40), (40, 6907))
```

After the factorization, we try to reconstruct the original matrix by multiplying its factors.

- No sparsity any more. It generates predictions for items the user has not interacted with, which we will exploit for recommendations.

In [151…]:

```python
all_user_predicted_ratings = np.dot(np.dot(U, sigma), Vt)
all_user_predicted_ratings
```

Out[151]:

```
array([[ 0.02292273,  0.01838176,  0.0042864 , ...,  0.01090701,
         0.05341585,  0.01885435],
       [-0.03654072, -0.02313435, -0.03319799, ...,  0.02337009,
        -0.00532303, -0.00283612],
       [ 0.00239874, -0.01840318, -0.02263362, ...,  0.00563758,
         0.11668636, -0.05929882],
       ...,
       [-0.02380071, -0.01779677, -0.01164514, ..., -0.00719634,
         0.01912133,  0.64562998],
       [ 0.10246305,  0.02996917,  0.07688153, ...,  0.15951745,
         0.38916266, -0.06106651],
       [ 0.0035282 ,  0.09884057,  0.13012081, ...,  0.14979794,
         0.49248323,  0.28502441]])
```

Normalize the ratings

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

In [152…]:

```python
all_user_predicted_ratings_norm = (all_user_predicted_ratings - all_user_predicted_ratings.min()) / \
                                  (all_user_predicted_ratings.max() - all_user_predicted_ratings.min())
```

In [153…]:

```python
# Converting the reconstructed matrix back to a Pandas dataframe
cf_preds_df = pd.DataFrame(all_user_predicted_ratings_norm, columns = users_items_pivot_matrix_df.columns, inde
cf_preds_df.head(10)
```

Out[153]:

	17	87	192	308	330	383	421	486	523	612	...	26672	26764	26788	268
Uid															
1	0.209621	0.202702	0.207233	0.256061	0.154096	0.200324	0.202197	0.211589	0.209084	0.255863	...	0.224655	0.219448	0.229545	0.3014
2	0.209092	0.204262	0.204813	0.216671	0.184733	0.207697	0.195703	0.219007	0.212960	0.207962	...	0.208117	0.209986	0.230314	0.2626
5	0.207452	0.203091	0.204320	0.196924	0.180002	0.208463	0.226422	0.219798	0.214746	0.189833	...	0.214457	0.186152	0.237972	0.3168
6	0.206838	0.203575	0.202876	0.165002	0.172763	0.195258	0.213597	0.208480	0.208221	0.221522	...	0.207416	0.211785	0.236875	0.3646
11	0.202818	0.206896	0.200204	0.187011	0.227901	0.224145	0.214796	0.220232	0.204843	0.371452	...	0.219410	0.227331	0.200532	0.1130
13	0.207045	0.206528	0.206573	0.206293	0.211204	0.206923	0.215997	0.207239	0.207677	0.210887	...	0.208789	0.210739	0.205920	0.1986
21	0.207602	0.219221	0.200512	0.258154	0.170454	0.203612	0.238084	0.208334	0.204967	0.237605	...	0.203969	0.177954	0.206309	0.2274
22	0.207662	0.209752	0.204168	0.205712	0.185924	0.204183	0.196128	0.208172	0.206436	0.248826	...	0.210740	0.195485	0.209730	0.1988
24	0.202855	0.212751	0.202912	0.199510	0.233671	0.197231	0.196826	0.206458	0.208081	0.193236	...	0.208867	0.204131	0.217123	0.1826
25	0.204601	0.213617	0.210699	0.206744	0.211300	0.201049	0.201495	0.207056	0.208858	0.199133	...	0.207029	0.196515	0.215327	0.1938

10 rows × 449 columns

```
class CFRecommender:

    MODEL_NAME = 'Collaborative Filtering'

    def __init__(self, cf_predictions_df, items_df=None):
        self.cf_predictions_df = cf_predictions_df
        self.items_df = items_df

    def get_model_name(self):
        return self.MODEL_NAME

    def recommend_items(self, user_id, items_to_ignore=[], topn=10, verbose=False):
        # Get and sort the user's predictions
        sorted_user_predictions = self.cf_predictions_df[user_id].sort_values(ascending=False) \
                                    .reset_index().rename(columns={user_id: 'Review_Rating'})

        # Recommend the highest predicted rating movies that the user hasn't seen yet.
        recommendations_df = sorted_user_predictions[~sorted_user_predictions['Uid'].isin(items_to_ignore)] \
                               .sort_values('Review_Rating', ascending = False) \
                               .head(topn)

        if verbose:
            if self.items_df is None:
                raise Exception('"items_df" is required in verbose mode')

            recommendations_df = recommendations_df.merge(self.items_df, how = 'left',
                                                          left_on = 'Uid',
                                                          right_on = 'Uid')[['Review_Rating', 'Uid', 'title']]


        return recommendations_df
```

```
cf_recommender_model = CFRecommender(cf_preds_df, books_selected)
```

```
print('Evaluating Collaborative Filtering (SVD Matrix Factorization) model...')
cf_global_metrics, cf_detailed_results_df = model_evaluator.evaluate_model(cf_recommender_model)

print('\nGlobal metrics:\n%s' % cf_global_metrics)
cf_detailed_results_df.head(10)
```

```
Evaluating Collaborative Filtering (SVD Matrix Factorization) model...
448 users processed

Global metrics:
{'modelName': 'Collaborative Filtering', 'recall@5': 0.30488305293393514, 'recall@10': 0.41991519627957874}
```

	hits@5_count	hits@10_count	interacted_count	recall@5	recall@10	_person_id
35	25	36	76	0.328947	0.473684	15602
31	21	26	70	0.300000	0.371429	17161
11	18	27	69	0.260870	0.391304	2557
168	30	39	63	0.476190	0.619048	1863
87	18	27	63	0.285714	0.428571	7740
20	16	20	62	0.258065	0.322581	26336
156	18	25	62	0.290323	0.403226	22026
61	5	12	61	0.081967	0.196721	421
276	24	33	60	0.400000	0.550000	16300
83	15	31	56	0.267857	0.553571	16765

Evaluating the Collaborative Filtering model (SVD matrix factorization), we observe that we got **Recall@5 ≈ 30.49%** and **Recall@10 ≈ (41.99%)**.

Next we iterate over a list of the number of factors to find the best number of factors k

```
num_factor = np.linspace(10, 100, 91, dtype='int64')

global_recall_5 = []
global_recall_10 = []

for n in num_factor:
    print("Number of factor is: ", n)
    U, sigma, Vt = svds(users_items_pivot_sparse_matrix, k = n)
    sigma = np.diag(sigma)

    all_user_predicted_ratings = np.dot(np.dot(U, sigma), Vt)
    all_user_predicted_ratings_norm = (all_user_predicted_ratings - all_user_predicted_ratings.min()) / \
                                      (all_user_predicted_ratings.max() - all_user_predicted_ratings.min())

    cf_preds_df = pd.DataFrame(all_user_predicted_ratings_norm, columns = users_items_pivot_matrix_df.columns,

    # build model
    cf_recommender_model = CFRecommender(cf_preds_df, books_selected)
    cf_global_metrics, _ = model_evaluator.evaluate_model(cf_recommender_model)

    global_recall_5.append(cf_global_metrics['recall@5'])
    global_recall_10.append(cf_global_metrics['recall@10'])
```

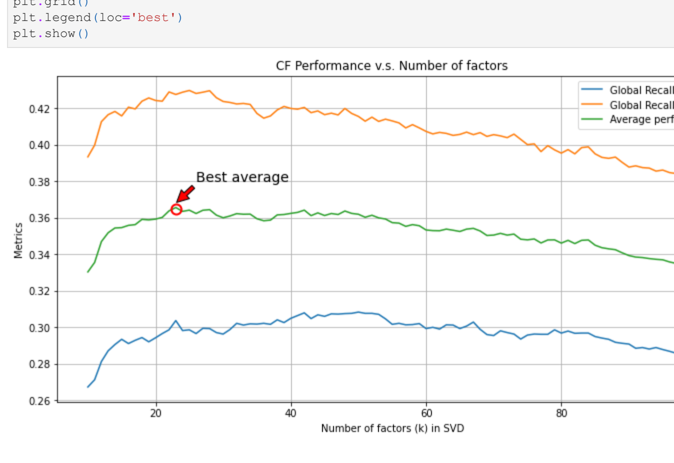
Plot the metric performance v.s. number of factors (k)

```
# compute the average of Recall@5 & Recall@10
average_metric = 0.5 * (np.array(global_recall_5) + np.array(global_recall_10))

plt.figure(figsize=(12, 6))
plt.plot(num_factor, global_recall_5, label = 'Global Recall@5')
plt.plot(num_factor, global_recall_10, label = 'Global Recall@10')
plt.plot(num_factor, average_metric, label = 'Average performance')

plt.plot(23, 0.365, 'o', ms=5 * 2, mec='red', mfc='none', mew=2)
plt.annotate('Best average', xy=(23, 0.368), xytext=(26, 0.38), fontsize=14,
             arrowprops=dict(facecolor='red', shrink=0.04))

plt.title('CF Performance v.s. Number of factors')
plt.xlabel('Number of factors (k) in SVD')
plt.ylabel('Metrics')
plt.grid()
plt.legend(loc='best')
plt.show()
```



Find the optimal number of factors based on the average performance of metrics

```
index = average_metric.argmax()
k_optimal = num_factor[index]

print("The best number of factor k = ", k_optimal)
print("The corresponding Recall@5 = ", global_recall_5[index])
print("The corresponding Recall@10 = ", global_recall_10[index])
```

```
The best number of factor k =  23
The corresponding Recall@5 =  0.3036520311858843
The corresponding Recall@10 =  0.4275748871563398
```

```
# maximum of two metrics, we can see no large differences with our chosen optimal k
np.max(global_recall_5), np.max(global_recall_10)
```

```
(0.30830255778963206, 0.42976337026398576)
```

Re-train the model with optimal k = 23

```
U, sigma, Vt = svds(users_items_pivot_sparse_matrix, k = k_optimal)
sigma = np.diag(sigma)

all_user_predicted_ratings = np.dot(np.dot(U, sigma), Vt)
all_user_predicted_ratings_norm = (all_user_predicted_ratings - all_user_predicted_ratings.min()) / \
                                  (all_user_predicted_ratings.max() - all_user_predicted_ratings.min())

cf_preds_df = pd.DataFrame(all_user_predicted_ratings_norm, columns = users_items_pivot_matrix_df.columns, inde

# build model
cf_recommender_model = CFRecommender(cf_preds_df, books_selected)

print('Evaluating Collaborative Filtering (SVD Matrix Factorization) model...')
cf_global_metrics, cf_detailed_results_df = model_evaluator.evaluate_model(cf_recommender_model)

print('\nGlobal metrics:\n%s' % cf_global_metrics)
cf_detailed_results_df.head(10)
```

```
Evaluating Collaborative Filtering (SVD Matrix Factorization) model...
448 users processed

Global metrics:
{'modelName': 'Collaborative Filtering', 'recall@5': 0.3036520311858843, 'recall@10': 0.4275748871563398}
```

	hits@5_count	hits@10_count	interacted_count	recall@5	recall@10	_person_id
35	28	40	76	0.368421	0.526316	15602
31	24	31	70	0.342857	0.442857	17161
11	22	29	69	0.318841	0.420290	2557
168	28	35	63	0.444444	0.555556	1863
87	20	33	63	0.317460	0.523810	7740
20	21	34	62	0.338710	0.548387	26336
156	25	29	62	0.403226	0.467742	22026
61	15	21	61	0.245902	0.344262	421
276	23	31	60	0.383333	0.516667	16300
83	23	29	56	0.410714	0.517857	16765

The optimal collaborative filtering model with $k = 23$ demonstrates **Recall@5 ≈ 30.37%** and **Recall@10 ≈ 42.76%**. Also a great improvement from the baseline, but a little bit inferior to our content-based filtering model, possibly due to the great sparsity nature of our dataset. Methods like SVD, which are based on some mathematical theories might not be able to take account of too many 'exceptions' in review ratings in real world.

2.4 Hybrid model (Content-based + Collaborative filtering)

- Combine pervious two models: **Content-based filtering** & **Collaborative filtering** together as a hybrid model
- We anticipate these kind of ensembing models will produce a better result than single models

```
class HybridRecommender:

    MODEL_NAME = 'Hybrid'

    def __init__(self, cb_rec_model, cf_rec_model, items_df, cb_ensemble_weight=1.0, cf_ensemble_weight=1.0):
        self.cb_rec_model = cb_rec_model
        self.cf_rec_model = cf_rec_model
        self.cb_ensemble_weight = cb_ensemble_weight  # weight of content-based filtering
        self.cf_ensemble_weight = cf_ensemble_weight  # weight of collaborative filtering
        self.items_df = items_df

    def get_model_name(self):
        return self.MODEL_NAME

    def recommend_items(self, user_id, items_to_ignore=[], topn=10, verbose=False):
        # Getting the top-1000 Content-based filtering recommendations
        cb_recs_df = self.cb_rec_model.recommend_items(user_id, items_to_ignore=items_to_ignore, verbose=verbos
                                                       topn=1000).rename(columns={'Review_Rating': 'Rating_

        # Getting the top-1000 Collaborative filtering recommendations
        cf_recs_df = self.cf_rec_model.recommend_items(user_id, items_to_ignore=items_to_ignore, verbose=verbos
                                                       topn=1000).rename(columns={'Review_Rating': 'Rating_

        # Combining the results by Uid
        recs_df = cb_recs_df.merge(cf_recs_df,
                                   how = 'outer',
                                   left_on = 'Uid',
                                   right_on = 'Uid').fillna(0.0)

        # Computing a hybrid recommendation score based on CF and CB scores
        recs_df['Rating_Hybrid'] = (recs_df['Rating_CB'] * self.cb_ensemble_weight) \
                                   + (recs_df['Rating_CF'] * self.cf_ensemble_weight)

        # Sorting recommendations by hybrid score
        recommendations_df = recs_df.sort_values('Rating_Hybrid', ascending=False).head(topn)

        if verbose:
            if self.items_df is None:
                raise Exception('"items_df" is required in verbose mode')

            recommendations_df = recommendations_df.merge(self.items_df, how = 'left',
                                                          left_on = 'Uid',
                                                          right_on = 'Uid')[['Rating_Hybrid', 'Uid', 'Title']]


        return recommendations_df
```

We first simply use the balanced weights 1 : 1 for two models

- You can choose optimal weights by trial and error, or use linear regression to study the optimal weights

```
hybrid_recommender_model = HybridRecommender(content_based_recommender_model, cf_recommender_model, books_selec
                                             cb_ensemble_weight=1.0, cf_ensemble_weight=1.0)
```

```
print('Evaluating Hybrid model...')
hybrid_global_metrics, hybrid_detailed_results_df = model_evaluator.evaluate_model(hybrid_recommender_model)

print('\nGlobal metrics:\n%s' % hybrid_global_metrics)
hybrid_detailed_results_df.head(10)
```

```
Evaluating Hybrid model...
448 users processed

Global metrics:
{'modelName': 'Hybrid', 'recall@5': 0.515387771850636, 'recall@10': 0.6209820817945562}
```

	hits@5_count	hits@10_count	interacted_count	recall@5	recall@10	_person_id
35	39	46	76	0.513158	0.605263	15602
31	29	39	70	0.414286	0.557143	17161
11	25	38	69	0.362319	0.550725	2557
168	30	37	63	0.476190	0.587302	1863
87	28	36	63	0.444444	0.571429	7740
20	31	40	62	0.500000	0.645161	26336
156	26	32	62	0.419355	0.516129	22026
61	15	22	61	0.245902	0.360656	421
276	30	35	60	0.500000	0.583333	16300
83	21	32	56	0.375000	0.571429	16765

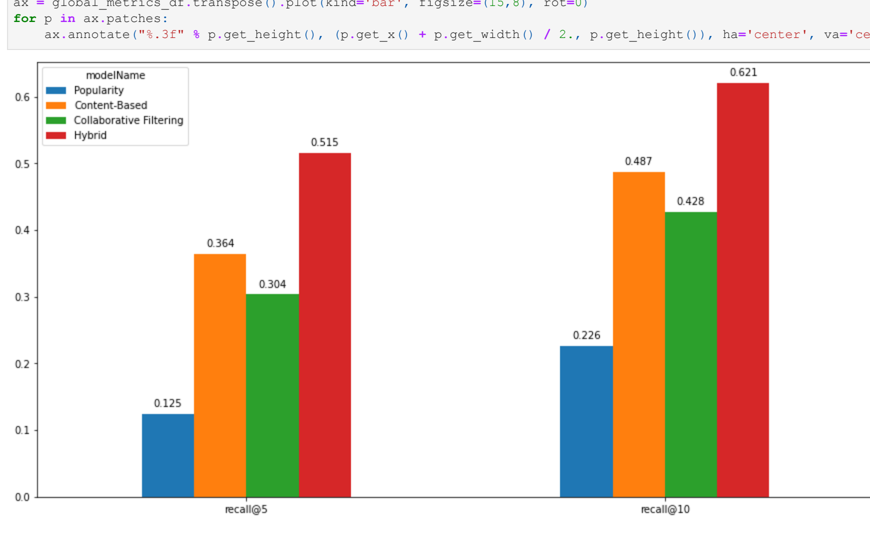
Comparing these models' performance

```
global_metrics_df = pd.DataFrame([pop_global_metrics, cb_global_metrics, cf_global_metrics, hybrid_global_metri
                        .set_index('modelName')
global_metrics_df
```

modelName	recall@5	recall@10
Popularity	0.124573	0.226173
Content-Based	0.363873	0.486941
Collaborative Filtering	0.303652	0.427575
Hybrid	0.515388	0.620982

Generally we can observe the highest performance in our final hybrid model

```
%matplotlib inline
ax = global_metrics_df.transpose().plot(kind='bar', figsize=(15,8), rot=0)
for p in ax.patches:
    ax.annotate("%.3f" % p.get_height(), (p.get_x() + p.get_width() / 2., p.get_height()), ha='center', va='cen
```



Though our models demonstrate some impressive results, but we should also pay attention to some potential limitations:

- Here we use **Recall@N** to measure the performance of models, but imagine for some 'extreme' user who is almost always being critical to books (i.e. always posts negative reviews), then our model only learns from the books **relevant** to him and it will be quitely likely to recommend books that might not be the real favor of him.

- This can be extends to the *cold-start* problem for new users, if you only know one rating from this new user and that rating happens to be negative, the recommendation models might not work that well as desired;

- Therefore, currently we use users with at least 40 ratings, but we will try to test our trained models on users with less ratings (eliminated before) to simulate this situation and see how our models work and discuss potential ways to advance performance.

Part 3) Natural Language Processing (NLP) models

In this part, we consider some NLP models to prepare for the interaction tools that will be presented in the next module. The main functions are as follows:

- **Tag filtering system**: we want to extract ***tags*** for each book to enable users to filter books & comments by tags
  - **Topic Modeling** (Section 3.2): LDA method
  - **Keywords Extraction** (Section 3.3): TextRank
  - **Keyphrases Extraction** (Section 3.4): Yake!, keyBERT, Rake, etc.

- **Extractive Summarization** (Section 3.5): Extract top review sentences to serve as a ***summary*** of all reviews of each book
  - Baseline approach
  - Balanced summarization

```
import pandas as pd
import numpy as np
import os
import re

import warnings
warnings.filterwarnings("ignore")
```

3.1 Texts Pre-processing

Before we start the NLP models, we first conduct some pre-processing on our review content

Load the review dataset

```
df_reviews = pd.read_csv('./Datasets/Basic_datasets/Book_reviews_cleaned.csv')
df_reviews.head(5)
```

	Uid	Title	Reviewer	N_Review	N_Follower	Review_Rating	Review_Date	Content	N_Likes	N_Comments
0	13642600	A Splash of Red The Life and Art of Horace Pippin	Chaplain Walle	380	18	4	January 22, 2023	review later	22	0
1	13642600	A Splash of Red The Life and Art of Horace Pippin	Lisa	750	131	5	November 7, 2014	We enjoyed this beautifully illustrated book a...	11	2
2	13642600	A Splash of Red The Life and Art of Horace Pippin	Moonkiszt	1922	205	3	January 30, 2022	Featured in a grandma reads session.Exactly wh...	7	0
3	13642600	A Splash of Red The Life and Art of Horace Pippin	Cindy Newton	600	127	4	June 20, 2020	Cute nonfiction picture book over the life of ...	6	0
4	13642600	A Splash of Red The Life and Art of Horace Pippin	Agné	744	57	3	August 16, 2017	A Splash of Red: The Life and Art of Horace Pi...	6	9

Here for NLP models, we are more interested in the textual reviews left by users: `Content`

```
reviews = df_reviews[['Uid', 'Content']].copy()
reviews.head(5)
```

	Uid	Content
0	13642600	review later
1	13642600	We enjoyed this beautifully illustrated book a...
2	13642600	Featured in a grandma reads session.Exactly wh...
3	13642600	Cute nonfiction picture book over the life of ...
4	13642600	A Splash of Red: The Life and Art of Horace Pi...

Clean the reviews content

- Lowercase
- Remove punctuation
- Remove digits
- Remove stopwords & frequent but less meaningful words

```
from string import punctuation

def remove_punctuation(document):
    no_punct_char = []
    for character in document:
        # replace sentence separation punctuation by empty char
        if character in [',', '.', '?', ';']:
            no_punct_char.append(' ')
            continue

        if character not in punctuation:
            no_punct_char.append(character)

    no_punct = ''.join(no_punct_char)

    return no_punct


def remove_digit(document):
    no_digit = ''.join([character for character in document if not character.isdigit()])
    return no_digit
```

```
reviews['Content'] = reviews['Content'].apply(str.lower) # lower case
reviews['Content'] = reviews['Content'].apply(remove_punctuation)
reviews['Content'] = reviews['Content'].apply(remove_digit)
```

```
reviews.head()
```

	Uid	Content
0	13642600	review later
1	13642600	we enjoyed this beautifully illustrated book a...
2	13642600	featured in a grandma reads session exactly wh...
3	13642600	cute nonfiction picture book over the life of ...
4	13642600	a splash of red the life and art of horace pip...

Remove stopwords & frequent but less meaningful words

Here we define a **drop probability** (idea from inverse freuqncy used in TD-IDF) to detect high-frequency words as follows:

$$\mathbb{P}_{Drop} = 1 - \frac{t}{frequency}$$

where t is a very small number and we will drop the word has $\mathbb{P}_{Drop} >= threshold$ to recude model noise and accelerate training

```
import nltk
from nltk.corpus import stopwords

# nltk.download('stopwords')
stop_words = set(stopwords.words('english'))
stop_words.update(['book', 'one', 'br', 'much', 'story', 'say', 'im', 'ive'])
```

```
from collections import Counter
from itertools import chain

def remove_stopwords(reviews):
    return [[word for word in simple_preprocess(str(review)) if word not in stop_words] for review in reviews]

# some words might appear too frequnetly but less meaningful, we also remove them
def remove_frequency_stop_words(reviews):
    t = 1e-5  # t-value
    threshold = 0.8  # threshold
    word_list = list(chain(*reviews)) # use chain() to combine all words

    # calculate word frequency
    int_word_counts = Counter(word_list)
    total_count = len(word_list)
    word_freqs = {w: c / total_count for w, c in int_word_counts.items()}

    # calculate the drop probability for words
    prob_drop = {w: 1 - np.sqrt(t / f) for w, f in word_freqs.items()}

    # if drop probability < threshold, we keep this word for training
    train_words = []
    for i in range(len(reviews)):
        train_words.append([w for w in reviews[i] if prob_drop[w] < threshold])

    return train_words
```

We first need to tokenize the reviews to remove stopwords

```
from gensim.utils import simple_preprocess

def tokenize_reviews(reviews):
    for review in reviews:
        # deacc=True removes punctuations
        yield(simple_preprocess(str(review), deacc=True))
```

```
review_list = reviews['Content'].values.tolist()
tokenized_reviews = list(tokenize_reviews(review_list))
```

```
tokenized_reviews[1][:20]
```

```
['we',
 'enjoyed',
 'this',
 'beautifully',
 'illustrated',
 'book',
 'about',
 'the',
 'life',
 'of',
 'horace',
 'pippin',
 'sometimes',
 'when',
 'we',
 'finish',
 'reading',
 'really',
 'good',
 'book']
```

```
# remove stop words & too frequent words
train_words = remove_stopwords(tokenized_reviews)
train_words = remove_frequency_stop_words(train_words)
```

We can observe that, some less meaningful stopwords like: 'we', 'book', 'somtimes', 'this', etc. has been removed

```
train_words[1][:20]
```

```
['beautifully',
 'illustrated',
 'horace',
 'pippin',
 'finish',
 'google',
 'investigate',
 'horace',
 'pippin',
 'artist',
 'admire',
 'perseverance',
 'courage',
 'google',
 'horace',
 'pippin',
 'selftaught',
 'painter',
 'unanimous',
 'eggers']
```

Replace original review texts with stopwords removed and detokenize to sentences

```
reviews['Content'] = train_words
```

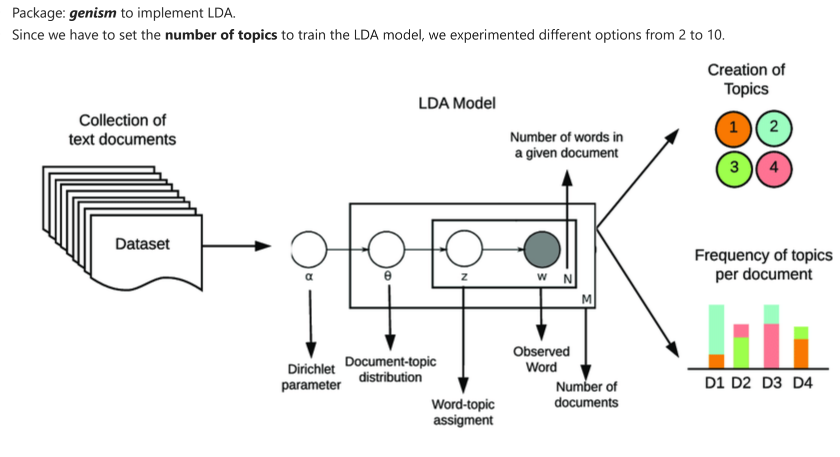
```
from nltk.tokenize.treebank import TreebankWordDetokenizer

reviews['Content'] = reviews['Content'].apply(TreebankWordDetokenizer().detokenize)
```

3.2 Topic Modelling: Latent Dirichlet Allocation (LDA)

Latent Dirichlet Allocation (LDA) is an unsupervised learning method that helps us to assign document to a particular set of topics and each topic will be characterized by a particular set of words.

- Package: ***genism*** to implement LDA.
- Since we have to set the **number of topics** to train the LDA model, we experimented different options from 2 to 10.



To build LDA model, we first need to extact a corpus from our review data

- We first use ***gensim.corpora.Dictionary()***: map each normalized words with an integer ids as a dictionary
- Then we use ***.doc2bow()*** to convert document (a list of words) into the ***bag-of-words*** format: list of (token_id, token_count) 2-tuples.

```
from gensim import corpora

def corpus_prepare(words_list):

    # Create Dictionary
    id2word = corpora.Dictionary(words_list)
    # Create Corpus: Term Document Frequency
    corpus = [id2word.doc2bow(word) for word in words_list]

    return id2word, corpus
```

```
id2word, review_corpus = corpus_prepare(train_words)
```

Build the LDA model

Here by default we set **verbose=False** because the model might need a long time for training, if you want to train by yourself, just turn **verbose=True**

```
from gensim.models import LdaMulticore
from pprint import pprint
import pyLDAvis.gensim_models as gensimvis
import pickle
import pyLDAvis

def lda_basic(word_dict, corpus, num_topics, verbose=False):

    # Build LDA model
    lda_model = LdaMulticore(corpus=corpus,
                             id2word=word_dict,
                             num_topics=num_topics)
    # Print the keywords in the 10 topics
    pprint(lda_model.print_topics())
    doc_lda = lda_model[corpus]

    # Visualize the topics
    # pyLDAvis.enable_notebook()
    filepath = './output/ldavis_prepared_' + str(num_topics)

    # This is a bit time consuming - make verbose = True
    # if you want to execute visualization prep yourself
    if verbose:
        LDAvis_prepared = gensimvis.prepare(topic_model=lda_model,
                                            corpus=corpus, dictionary=word_dict)
        with open(filepath, 'wb') as f:
            pickle.dump(LDAvis_prepared, f)

    else:
        # load the pre-prepared pyLDAvis data from disk
        with open(filepath, 'rb') as f:
            LDAvis_prepared = pickle.load(f)

    # store html result
    pyLDAvis.save_html(LDAvis_prepared, './output/ldavis_content_' + str(num_topics) +'.html')
```

This process might be time-consuming, we recommend to directly use our results

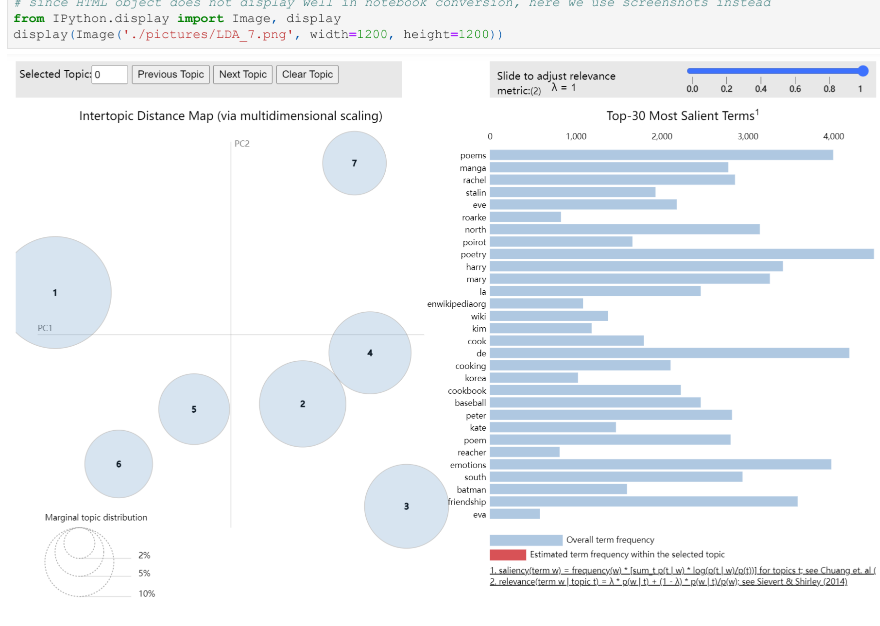
```
for i in range(2, 11):
    lda_basic(word_dict=id2word, corpus=review_corpus, num_topics=i, verbose=False)
```

After comparison of different topic numbers, we recognize when topic number = 7, LDA produces the best classification

```
from IPython.display import display, HTML
display(HTML("<style>.container { max-width:100% !important; }</style>"))
display(HTML("<style>.output_result { max-width:100% !important; }</style>"))
display(HTML("<style>.output_area { max-width:100% !important; }</style>"))
display(HTML("<style>.input_area { max-width:100% !important; }</style>"))

filepath = './output/ldavis_content_7.html'
display(HTML(filepath))
```

```
# since HTML object does not display well in notebook conversion, here we use screenshots instead
from IPython.display import Image, display
display(Image('./pictures/LDA_7.png', width=1200, height=1200))
```

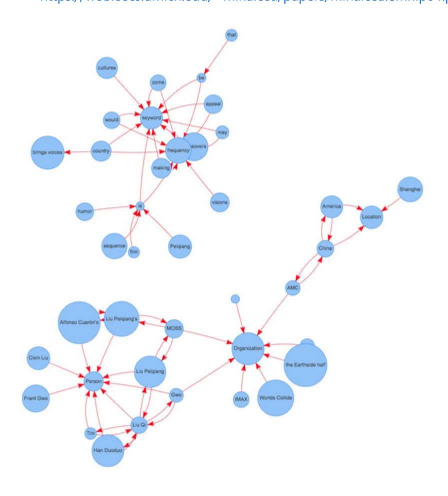


However, the problem is that the topic of each cluster is *ambiguous*, thus we cannot decide a specific topic name for each cluster. So we change our mind to extract the keywords for each book instead of all the books together.

3.3 Keyword Extraction: *TextRank*

TextRank – is a graph-based ranking model for text processing which can be used to find the **most relevant** sentences or keywords in text

- Idea similar to **PageRank**, a powerful serach engine algorithm
- https://web.eecs.umich.edu/~mihalcea/papers/mihalcea.emnlp04.pdf



First we combine reviews for each book

```
from tqdm import tqdm

book_dict = {}
for index, row in tqdm(reviews.iterrows()):
    key = row['Uid']
    if key not in book_dict:
        comments = ' '
        comments += row['Content']
        book_dict[key] = comments
    else:
        book_dict[key] += ' ' + row['Content']

df_comments = pd.DataFrame.from_dict(book_dict, orient='index', columns=['Content'])
```

```
114034it [00:03, 32956.87it/s]
```

```
df_comments.reset_index(inplace=True)
df_comments.rename(columns = {'index':'Uid'}, inplace=True)

df_comments.head()
```

	Uid	Content
0	13642600	beautifully illustrated horace pippin finish...
1	470185	strangest months suddenly appear everywhere k...
2	137933	philosophers tend worst theorist artists tend...
3	52374	wideranging debut essays film stimulating rel...
4	140987	introduced dave hickey painting classes profe...

Build the *TextRank* model

- Because most of the words in a sentence are not useful to determine the importance, we only consider the words with **NOUN & ADJ** tags
- Each word is a ***node*** in PageRank and if we set the window size as k, the window will like following:
  - $Word\ vector : [w_1, w_2, \ldots, w_n]$
  - $[w_1, w_2, \ldots, w_k], [w_2, w_3, \ldots, w_{k+1}], \ldots$ are corresponding windows with size k

In [169…

```python
from collections import OrderedDict
import numpy as np
import spacy
from spacy.lang.en.stop_words import STOP_WORDS
import string
from string import punctuation

nlp = spacy.load('en_core_web_sm')

class TextRank4Keyword():
    """Extract keywords from text"""

    def __init__(self):
        self.d = 0.85 # damping coefficient, usually is .85
        self.min_diff = 1e-5 # convergence threshold
        self.steps = 10 # iteration steps
        self.node_weight = None # save keywords and its weight


    def set_stopwords(self, stopwords):
        """Set stop words"""
        for word in STOP_WORDS.union(set(stopwords)):
            lexeme = nlp.vocab[word]
            lexeme.is_stop = True

    def sentence_segment(self, doc, candidate_pos, lower):
        """Store those words only in cadidate_pos"""
        sentences = []
        for sent in doc.sents:
            selected_words = []
            for token in sent:
                # Store words only with cadidate POS tag
                if token.pos_ in candidate_pos and token.is_stop is False:
                    if lower is True:
                        selected_words.append(token.text.lower())
                    else:
                        selected_words.append(token.text)
            sentences.append(selected_words)
        return sentences

    def get_vocab(self, sentences):
        """Get all tokens"""
        vocab = OrderedDict()
        i = 0
        for sentence in sentences:
            for word in sentence:
#                 if word in ('.','!','?',',','-','*'):
#                     continue
                if word not in vocab:
                    vocab[word] = i
                    i += 1
        return vocab

    def get_token_pairs(self, window_size, sentences):
        """Build token_pairs from windows in sentences"""
        token_pairs = list()
        for sentence in sentences:
            for i, word in enumerate(sentence):
#                 if word in ('.','!','?',',','-','*'):
#                     continue
                for j in range(i+1, i+window_size):
                    if j >= len(sentence):
                        break
                    pair = (word, sentence[j])
                    if pair not in token_pairs:
                        token_pairs.append(pair)
        return token_pairs

    def symmetrize(self, a):
        return a + a.T - np.diag(a.diagonal())

    def get_matrix(self, vocab, token_pairs):
        """Get normalized matrix"""
        # Build matrix
        vocab_size = len(vocab)
        g = np.zeros((vocab_size, vocab_size), dtype='float')
        for word1, word2 in token_pairs:
            i, j = vocab[word1], vocab[word2]
            g[i][j] = 1

        # Get Symmeric matrix
        g = self.symmetrize(g)

        # Normalize matrix by column
        norm = np.sum(g, axis=0)
        g_norm = np.divide(g, norm, where=norm!=0) # this is ignore the 0 element in norm

        return g_norm


    def get_keywords(self, number=10):
        """Print top number keywords"""
        keywords_list = []
        node_weight = OrderedDict(sorted(self.node_weight.items(), key=lambda t: t[1], reverse=True))
        for i, (key, value) in enumerate(node_weight.items()):
            if key not in list(string.punctuation):
                keywords_list.append(key)
            if i > number:
                break
        return keywords_list


    def analyze(self, text,
                candidate_pos=['NOUN', 'ADJ','VERB'],
                window_size=4, lower=False, stopwords=list()):

        """Main function to analyze text"""
        self.set_stopwords(stopwords)

        # Pare text by spaCy
        doc = nlp(text)

        # Filter sentences
        sentences = self.sentence_segment(doc, candidate_pos, lower) # list of list of words

        # Build vocabulary
        vocab = self.get_vocab(sentences)

        # Get token_pairs from windows
        token_pairs = self.get_token_pairs(window_size, sentences)

        # Get normalized matrix
        g = self.get_matrix(vocab, token_pairs)

        # Initionlization for weight(pagerank value)
        pr = np.array([1] * len(vocab))

        # Iteration
        previous_pr = 0
        for epoch in range(self.steps):
            pr = (1-self.d) + self.d * np.dot(g, pr)
            if abs(previous_pr - sum(pr))  < self.min_diff:
                break
            else:
                previous_pr = sum(pr)

        # Get weight for each node
        node_weight = dict()
        for word, index in vocab.items():
            node_weight[word] = pr[index]

        self.node_weight = node_weight
```

We try with example book (Uid = 449128): *Alla Prima: Everything I Know about Painting*

- Window size k = 4, only consider NOUN & ADJ words
- We can see it generally catches important words like: **artist, patinting, canvas, color**, etc.

In [170…

```python
df_comments.iloc[5, 0]
```

Out[170]:

```
449128
```

In [171…

```python
text = df_comments.iloc[5, 1]

tr4w = TextRank4Keyword()

# we only want adjective & Nouns for tags
tr4w.analyze(text, candidate_pos = ['ADJ','NOUN'], window_size=4, lower=False)
tr4w.get_keywords(10)
```

Out[171]:

```
['artist',
 'advice',
 'color',
 'schmid',
 'painters',
 'confidence',
 'oil',
 'painting',
 'painter',
 'canvas',
 'artists',
 'composition']
```

We can also get each keyword's weights

In [173…

```python
[{key: tr4w.node_weight[key]} for key in tr4w.get_keywords(10)]
```

Out[173]:

```
[{'pippin': 9.081910937634829},
 {'horace': 7.501031593836607},
 {'artist': 3.9051219599946987},
 {'red': 2.845867898168256},
 {'pippins': 2.821484820122126},
 {'illustrations': 2.803523983238113},
 {'artists': 2.8025856402697573},
 {'artwork': 2.4789423374657984},
 {'painter': 2.3143430305118087},
 {'paintings': 2.2721199262405882},
 {'pictures': 2.267219780963017},
 {'notes': 2.0621940091953608}]
```

Next we used *TexRank* to extract 5 keywords of each book and classify each review to that tags if it contains the keyword

- The following process is time-consuming, just use our stored result datasets
  - **book_tags.csv**: 5 keywords tags for each book
  - **review_tags.csv**: keywords this review contains

In [ ]:

```python
# count how many reviews each book has
reviews_count = reviews.groupby(['Uid'], sort=False)['Uid'].count()

# add column 'Tags' if this review contains the keyword
reviews['Tags'] = [[] for _ in range(len(reviews))]
df_comments['Tags'] = [[] for _ in range(len(df_comments))]

num = 0 # the number of reviews we have classified
for i in tqdm(range(df_comments.shape[0])):
    print("The %d-th book" % i)
    text = df_comments.iloc[i, 1] # loop over each book

    # get 5 keywords
    tr4w = TextRank4Keyword()
    tr4w.analyze(text, candidate_pos = ['ADJ', 'NOUN'], window_size=4, lower=False)
    keyword_list = tr4w.get_keywords(5)

    # for each book, store their keywords from reviews
    df_comments['Tags'][i] = keyword_list

    # for each review, assign their tags if containing the keyword
    for _ in range(reviews_count.values[i]):
        tag_list = []
        for key in keyword_list:
            if key in reviews.iloc[num,1].split():
                tag_list.append(key)

        if not tag_list:
            num += 1
            continue
        print(tag_list)
        reviews['Tags'][num] = tag_list
        num = num + 1
```

We look at the tag extracted results

In [198…

```python
# each book's keywords (tags)
df_comments.head(8)
```

Out[198]:

	Uid	Content	Tags
0	13642600	beautifully illustrated horace pippin finish...	[pippin, horace, artist, red, pippins, illustr...
1	470185	strangest months suddenly appear everywhere k...	[animals, essays, animal, photography, berger,...
2	137933	philosophers tend worst theorist artists tend...	[artists, philosophical, artist, criticism, co...
3	52374	wideranging debut essays film stimulating rel...	[sontag, interpretation, essays, criticism, in...
4	140987	introduced dave hickey painting classes profe...	[basketball, essays, hickey, criticism, hickey...
5	449128	painter master artists richard schmid artists...	[artist, advice, color, schmid, painters, conf...
6	51245	included utter zoothe blue aspicthe epiplecti...	[gorey, goreys, legacy, blue, loathsome, utter...
7	47559	convey joy edward goreys adore unstrung harp ...	[gorey, hapless, tinies, drawings, gashlycrumb...

In [180…

```python
# each review's tags (if containing the book's keywords)
reviews.head(8)
```

Out[180]:

	Uid	Content	Tags
0	13642600		[]
1	13642600	beautifully illustrated horace pippin finish g...	[pippin, horace, artist]
2	13642600	featured grandma reads session splash red hora...	[pippin, horace, red, artists]
3	13642600	cute nonfiction artist horace pippin grad clas...	[pippin, horace, artist]
4	13642600	splash red horace pippin wellresearched pictur...	[pippin, horace, red, illustrations]
5	13642600	jen bryant illustrator melissa collaborated pi...	[pippin, horace, artist, red, artists]
6	13642600	audience primarygenre hisher talents splash re...	[pippin, horace, artist, red, illustrations]
7	13642600	aloud bryant obligations frequently artist rep...	[pippin, horace, artist, pippins, illustrations]

In [197…

```python
# store for use
df_comments.to_csv('./output/book_tags.csv')
reviews.to_csv('./output/review_tags.csv')
```

3.4 Other Trials: Key Phrases

We have also considered using **key phrases** instead of keywords as our tags and we have tried many methods like **Yake!, KeyBERT, Rake** etc. to extract keyphrases, but the phrases we got are not very meaningful as a tag.

We guess for these methods to get a better result, they might need more effort for tuning model parameters and improve the quality of original textual reviews, both could be time-consuming and no promise for final result. Therefore, we conclude these methods are not very suitable and finally reject them.

In [193…

```python
# previous tag result from TextRank
df_comments.iloc[3, 2]
```

Out[193]:

```
['sontag',
 'interpretation',
 'essays',
 'criticism',
 'intellectual',
 'essay',
 'content']
```

3.4.1 YAKE!

YAKE! is a light-weight unsupervised automatic keyword extraction method which rests on text **statistical features** extracted from single documents to select the most important keywords of a text.

In [185…

```python
import yake

# take one example
text = df_comments.iloc[3,1]
kw_extractor = yake.KeywordExtractor(top=10, n = 2, stopwords=None)
keywords = kw_extractor.extract_keywords(text)

for kw, v in keywords:
    print("Keyphrase: ",kw, ": score", v)
```

```
Keyphrase:  notes camp : score 0.00017788716562028035
Keyphrase:  susan sontag : score 0.0005297176952421673
Keyphrase:  essays susan : score 0.0007224643153954816
Keyphrase:  interpretation essays : score 0.0007676333810896728
Keyphrase:  sontag argues : score 0.0008288173643892819
Keyphrase:  films robert : score 0.0008668558595229885
Keyphrase:  sartres saint : score 0.0008950281626283484
Keyphrase:  saint genet : score 0.0009260733389271714
Keyphrase:  imagination disaster : score 0.0010521084810112312
Keyphrase:  interpretation sontag : score 0.0011256687586082986
```

According to the result, we could see there are some repetitions and overlaps across the phrases, which makes them hard to convey more diverse meanings and cause information redundancy, which is bad for tags selection.

3.4.2 TextRank (Summa)

The core method is the same as TextRank we used before. But this package is not that intelligent since there are so many repetition and it did not catch important information of book reviews.

In [186…

```python
from summa import keywords

text = df_comments.iloc[3,1]
TR_keywords = keywords.keywords(text, scores=True)
print(TR_keywords[0:10])
```

```
[('sontag', 0.4407184696812149), ('sontags', 0.4407184696812149), ('interpretation', 0.2987008422993689), ('cri
tic', 0.2654791090129931), ('criticized', 0.2654791090129931), ('essays film stimulating', 0.1835148264138276
3), ('interpretations cultured', 0.16760650948307876), ('interpret impoverish', 0.16343202148891145), ('critica
l takedown', 0.14618324210370381), ('essay notes camp remain', 0.14391607616789773)]
```

3.4.3 KeyBERT

KeyBERT is a simple, easy-to-use keyword extraction algorithm that takes advantage of SBERT embeddings to generate keywords and key phrases from a document that are more similar to the document.

- First, document embedding (a representation) is generated using the sentences-BERT model;
- Next, the embeddings of words are extracted for N-gram phrases. Computed cosine similarity of each keyphrase to the document;
- The most similar words can then be identified as the words that best describe the entire document and are considered as keywords.

Since BERT model need GPU, we put the result in the comments below.

In [ ]:

```python
from keybert import KeyBERT

text = df_comments.iloc[3,1]
kw_model = KeyBERT(model='all-mpnet-base-v2')
keywords = kw_model.extract_keywords(text,
                                     keyphrase_ngram_range=(1, 3),
                                     stop_words='english',
                                     highlight=False,
                                     top_n=10)

keywords_list= list(dict(keywords).keys())
print(keywords_list)
```

keywords_list: \ ['pippin art', 'pippin paintings', 'artist horace', 'pippin artist', 'horace pippin', 'pippin impressionistic', 'painter horace', 'evocative pippin', 'art horace', 'watercolor paintings']

The phrases are not very meaningful as tags because we can see too many common parts between these phrases (e.g. pippin), which might not be able to comprehensively reflect a book's attributes as tags.

3.4.4 Rake

Rake is short for ***Rapid Automatic Keyword Extraction*** - a method of extracting keywords from individual documents. It can also be applied to new fields very easily and is very effective in dealing with multiple types of documents, especially text that requires specific grammatical conventions.

Rake identifies key phrases in a text by analyzing the occurrence of a word and its compatibility with other words in the text (co-occurrence).

In [195…

```python
from multi_rake import Rake

text = df_comments.iloc[3,1]
rake = Rake()
keywords = rake.apply(text)
print(keywords[:10])
```

```
[('quarter petty ephemeral', 9.0), ('packaged sontag', 4.0), ('elevated', 1.0)]
```

We can see that most phrases are not very summative, the result is far away from satisfying.

3.5 Extract Summary for Reviews on Each Book

After we generate a list of recommended books, we want to help our book readers get a snapshot of what are the major opinions of other people who have reviewed the book. Thus, we aim to provide a summary of reviews on each book to help readers acquire the main ideas efficiently. We utilize **extractive summarization** method to extract top sentences from all reviews of a certain book and consider the top sentences as the summary. We explored the following two methods to extract the summary:

- **Method 1**: Baseline - LexRank + Sentence-BERT embedding
- **Method 2**: Improvement based on Method 1 to achieve three objectives
  - Maximize Centrality
  - Minimize Redundancy
  - Balance Sentiment

3.5.1 Method 1 - Baseline Model

- We firstly use **Sentence-BERT** to acquire sentence embeddings of each sentence
- Next, we use **LexRank** to get the graph-based "centrality" of each sentence. The higher the centrality score, the more prominent the sentence is to the whole review.
- Since **cosine similarity** allows us to approximate how similar two sentence vectors are by simply using the cosine of the angle between the two vectors to quantify how similar two sentences are, we calculate the cosine similarity of sentence embeddings from Sentence-BERT.
- If one sentence is similar to many other sentences in the review, we can claim that it is more central to the review or the "center" of the graph and thus it is more important.

In summary, for baseline model, we calculate **cosine similarity** of sentence embeddings from **Sentence-BERT** and extract **5 sentences** with the highest centrality scores as the summary.

Note: Our original code files need to run with GPU, thus we only put some code snippets and the results here as demonstration for the report.

In [ ]:

```python
from sentence_transformers import SentenceTransformer, util
from LexRank import degree_centrality_scores
from nltk.tokenize import sent_tokenize
from textblob import TextBlob

model = SentenceTransformer('sentence-transformers/paraphrase-mpnet-base-v2')
```

Build a pipeline function for generating summary of book reviews

In [ ]:

```python
def extract_summary(Uid, topk=5):

    # select all review sentences of a typical book with selected Uid
    sentences = sent_tokenize(df_comments[df_comments['Uid'] = Uid].Content)
    # we calculate the sentiment score using TextBlob, this measurement will be used as n evaluation metric lat
    sentiments = list(map(lambda text: TextBlob(text).sentiment.polarity, sentences))
    doc_sentiment = np.mean(sentiments)

    # Encode each sentence with Sentence-BERT
    sentence_embeddings = model.encode(sentences)
    # Calculate the cosine similarity scores among sentences
    cos_scores = util.cos_sim(sentence_embeddings, sentence_embeddings).numpy()
    # Obtain the centrality scores with LexRank
    centrality_scores = degree_centrality_scores(cos_scores, threshold=None)
    # We obtain the indexes of the most central sentences
    most_central_sentence_indices = np.argsort(-centrality_scores)
    summary_idxes = list(most_central_sentence_indices[:topk])

    # We use redundancy score as another evaluation metric
    def _compute_redundancy(idx, summary_idxes):
        if not summary_idxes: return 0
        return max([cos_scores[idx][senti] for senti in summary_idxes])

    # Store the outputs
    out_summary = ""
    out_sentiment = ""
    out_centralities = ""
    summary_sentiments = []
    summary_centralities = []
    summary_redundancies = []
    for idx in summary_idxes:
        summary_sentiments.append(sentiments[idx])
        summary_centralities.append(centrality_scores[idx])

        # compute redundancy of the specific sentence to all other sentences in the summary
        summary_idxes.remove(idx)
        redundancy = _compute_redundancy(idx, summary_idxes)
        summary_idxes.append(idx)
        summary_redundancies.append(redundancy)

        out_summary += sentences[idx] + "[SEP]"
        out_sentiment += str(sentiments[idx]) + "[SEP]"
        out_centralities += str(centrality_scores[idx]) + "[SEP]"

    mean_sentiment = np.mean(summary_sentiments)
    mean_centrality = np.mean(summary_centralities)
    mean_redundancy = np.mean(summary_redundancies)

    print(f"{mean_sentiment}, {mean_centrality}, {mean_redundancy}, {doc_sentiment}")

    return out_summary, out_sentiment, out_centralities, mean_sentiment, mean_centrality, mean_redundancy, doc_
```

Result demonstration

In [201…

```python
from IPython.display import Image, display
display(Image('./pictures/Baseline_output.png', width=1200, height=1200))
```

```
Summary:

A picture book bio about self-taught painter Horace Pippin. Score: 1.4652768018282623

A Splash of Red: The Life and Art of Horace Pippin is a well-researched picturebook biography of an esteemed self-taught African-American painter:Since I
knew nothing about Horace Pippin or his art before, I appreciated Jen Bryant's informative narrative. Score: 1.4332050402649952

Although the text is relatively brief, it contains quite a bit of information on African-American painter Horace Pippin, from his youth, to his service in
WWI, to his later success as a painter. Score: 1.4190988359182832

A Splash of Red: The Life and Art of Horace Pippin by Jen Bryant and illustrated by Melissa Sweet.NOTES: The colors are amazing. Score: 1.398752236549497
We think Horace Pippin was a great artist! Score: 1.3619491685051612

Grateful for the authors and illustrators who bring forward people, things, and experiences we might have missed in our patchwork educations.Cute
nonfiction picture book over the life of artist Horace Pippin. Score: 1.3615779259551986

It is a biography of Horace Pippin, an artist that I was unfamiliar with, but also a bit of a 'coming of age' book too as Horace tries different
occupations before and after the war before coming to the fact that he is, indeed, an artist. Score: 1.3609638761512897

review laterWe enjoyed this beautifully illustrated book about the life of Horace Pippin! Score: 1.3413680430242905

Eventually, his work was discovered and promoted by such figures as painter N.C. Wyeth, and he went on to become a well-known painter...I am so very glad
that I picked up A Splash of Red: The Life and Art of Horace Pippin, as I had not previously heard of this artist, but will now seek out more of his work.
Score: 1.3256232218563178

A gorgeous picture book about the life of Horace Pippin. Score: 1.319128407692399
```

However, after running the baseline model, we noticed some issues.

- First, there may be **different sentiment distribution** of extracted summary and original review texts of one book
  - Note: Sentiment scores are calculated using TextBlob Polarity Score (-1: Negative to 1: Positive)
  - For example, we may have mean sentiment of summary as 0.1565 and mean sentiment of original texts as 0.1217
- Second, there may be some **redundant information** among sentences in extracted summary
  - For example, for two sentences in the summary, they convey similar meanings
    - E.g. `Good book with clear structure!` & `Great book with organized structure!`
  - We want to try avoiding such redundancy and providing more diverse information to end users with the summary

To deal with the issues, we propose a more **balanced** summarization algorithm in method 2.

3.5.2 Method 2 - Improvement - Balanced Summarization

We use a greedy algorithm to extract a more balanced summary with **three objectives**

- **Maximize centrality score** which represents the importance of the sentence
- **Minimize** the difference between the summary sentiment and the overall sentiment of the original review texts
- **Minimize** the redundant information between extracted sentences

The learning objective of the model can be written as:

$$O(s, S, A) = Centrality(s), CosineSimilarity(s, S) - SentimentDifference(S \bigcup s, A)$$

where

- s represent the current review sentence,
- S is the target extracted summary, and
- A represents all the review texts of that specific book

Essentially, we want to extract a summary with high centrality, low redundancy, and a balanced sentiment.

The following is the code snippets of our improved algorithm.

In [ ]:

```python
def extract_summary_balanced(Uid, topk=5):

    """

    :param Uid:
    :param topk:
    :return: out_summary: summary string separated by [SEP]
            out_sentiment: sentiments string separated by [SEP]
            out_centralities: centrality score string separated by [SEP]
            mean_sentiment,
            mean_centrality,
            mean_redundancy,
            doc_sentiment: mean sentiment of original text score
    """

    # select sample review sentences
    sentences = sent_tokenize(df_comments[df_comments['Uid'] = Uid].Content)
    # we calculate the sentiment score using TextBlob, this measurement will be used as n evaluation metric
    sentiments = list(map(lambda text: TextBlob(text).sentiment.polarity, sentences))
    doc_sentiment = np.mean(sentiments)

    # Encode each sentence with Sentence-BERT
    sentence_embeddings = model.encode(sentences)
    # Calculate the cosine similarity scores among sentences
    cos_scores = util.cos_sim(sentence_embeddings, sentence_embeddings).numpy()
    # Obtain the centrality scores with LexRank
    centrality_scores = degree_centrality_scores(cos_scores, threshold=None)

    # We use redundancy score as another evaluation metric
    def _compute_redundancy(idx, summary_idxes):
        if not summary_idxes: return 0
        return max([cos_scores[idx][senti] for senti in summary_idxes])

    # We compute the sentiment score difference between the extracted summary and the original review text
    def _sentiment_difference(idx, summary_idxes):
        return abs(doc_sentiment - np.mean([sentiments[idx]] + [sentiments[senti] for senti in summary_idxes]))

    summary_idxes = []
    best_idx = None

    while len(summary_idxes) < topk and best_idx != -1:
        best_idx, best_objective = -1, -1000
        for idx in range(len(sentences)):
            if idx not in summary_idxes:
                redundancy = _compute_redundancy(idx, summary_idxes)
                sentiment_difference = _sentiment_difference(idx, summary_idxes)
                # maximizing centrality while minimizing redundancy and sentiment difference
                objective = centrality_scores[idx] - redundancy - sentiment_difference
                if objective > best_objective:
                    best_idx = idx
                    best_objective = objective
        if best_idx != -1:
            summary_idxes.append(best_idx)

    # Store the outputs
    out_summary = ""
    out_sentiment = ""
    out_centralities = ""
    summary_sentiments = []
    summary_centralities = []
    summary_redundancies = []

    for idx in summary_idxes:
        summary_sentiments.append(sentiments[idx])
        summary_centralities.append(centrality_scores[idx])

        # compute redundancy of the specific sentence to all other sentences in the summary
        summary_idxes.remove(idx)
        redundancy = _compute_redundancy(idx, summary_idxes)
        summary_idxes.append(idx)
        summary_redundancies.append(redundancy)

        out_summary += sentences[idx] + "[SEP]"
        out_sentiment += str(sentiments[idx]) + "[SEP]"
        out_centralities += str(centrality_scores[idx]) + "[SEP]"

    mean_sentiment = np.mean(summary_sentiments)
    mean_centrality = np.mean(summary_centralities)
    mean_redundancy = np.mean(summary_redundancies)

    print(f"{mean_sentiment}, {mean_centrality}, {mean_redundancy}, {doc_sentiment}")

    return out_summary, out_sentiment, out_centralities, mean_sentiment, mean_centrality, mean_redundancy, doc_
```

3.5.3 Result & Evaluation

Due to lack of gold summaries, we use **three metrics (Centrality, Sentiment Differences, and Redundancy)** of extracting the top 5 central sentences

- **Centrality**: Average centrality of summary sentences $->$ (Higher the better)
- **Sentiment Difference**: |mean of original text - mean of summary (sentiment)| $->$ (Lower the better)
- **Redundancy**: Average cosine similarity among summary sentences $->$ (Lower the better)

In [204…

```python
# Read result CSVs
summ_baseline = pd.read_csv('./output/summ-baseline-out.csv').iloc[:, 1:]  # baseline model
summ_balanced = pd.read_csv('./output/summ-balance-out.csv').iloc[:, 1:] # balanced model
```

We define an evaluation function to compute the above 3 metrics

In [230…

```python
def evaluation(name, stats_df):
    stats_df.replace(np.inf, np.nan, inplace=True) # replace 'inf' by 'NaN'
    stats_df.dropna(axis=0, how='any', inplace=True) # then drop all NaNs
    mean_df = stats_df.describe().loc['mean', :]

    print(name + " model metrics:")
    print("Centrality: ", mean_df['Mean_centrality'])
    print("Sentiment Difference: ", np.abs(mean_df['Mean_sentiment'] - mean_df['doc_sentiment']))
    print("Redundancy: ", mean_df['Mean_redundancy'])

    pass
```

In [231…

```python
evaluation("Baseline", summ_baseline.iloc[:, -4:])
```

```
Baseline model metrics:
Centrality:  1.457832593624464
Sentiment Difference:  0.034905608279972744
Redundancy:  0.65922499530985
```

In [233…

```python
evaluation("Balanced", summ_balanced.iloc[:, -4:])
```

```
Balanced model metrics:
Centrality:  1.407710446431976
Sentiment Difference:  0.006182471345803298
Redundancy:  0.5434062235968687
```

We summarize the metrics for two methods as follows:

	Baseline	Balanced Summarization
Centrality	**1.4578**	1.4077
Sentiment Difference	0.0349	**0.0062**
Redundancy	0.6592	**0.5434**

We can observe that, though sacrificing minor centrality, our Improvement method (Balanced Summarization Algorithm) achieved **lower sentiment difference** and **lower redundancy** than baseline method, generally a good result.

Part 4) Summary & Future plans

In this module, we first conduct some modifications on original datasets based on findings from exploratory data analysis and prepare it into a less sparse form for model part. Then we explore multiple recommendation models with optimizations that produce impressive results. Finally, we employ NLP models to provide more detailed information alongside books recommended to users, playing a role of user interaction tool and effective information extraction.

In the next module, we shall consider the following advancement and plans:

- **Ensemble model**: Currently we have considered several recommendation models and a hybrid one to combine them. Next we prepare to introduce some linear models that take book features & user features into consideration and then build a high-functional ensemble model as our final model;

- **NLP**: We will use NLP models to provide information overview of recommended book with our tags, summarization and sentiment scores. Then integrate models with interactive user interface to help users efficiently acquire information about books recommended to them

- **Interactive User interface**: In the next module, we will present an interactive user interface to play with our recommdendation system. It integrates recommendation models that produce to-read lists for users and use NLP models to provide information overview.

In [ ]: