BookReviews

November 8, 2020

0.1 Book Recommenders

using data from Book-Crossing: User review ratings

0.1.1 Introduction

The purpose of this project is to build a book recommendation system for the users of a social network website "BookCrossing.com". There are about one million book review data collected from the website. The dataset contains detailed information about the books, such as the title, the author, the year of publication, and so on. It also has some demographic information on the users, such as age and location. More importantly, the dataset has information on each user's ratings on every book they have read on the website. Using both the content-based filtering (TF-IDF vectorization) and the collaborative filtering algorithms (KNN), I was able to build book recommendations based on the users' preferences. The future plan for the project is as follows: (i) fine-tune the parameters of the algorithms and perform various validation to examine the performance of the recommendation systems; (ii) build a book recommendation system using hybrid filtering, that is, to combine the content-based and collaborative filtering algorithms, and (iii) build a small application that recommends books for the users.

[1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

0.1.2 1. Import the data

[2]:
```
#Users
u_cols = ['user_id', 'location', 'age']
users = pd.read_csv('../BookReview/Data/BX-Users.csv', sep=';', names=u_cols,␣
↪encoding='latin-1',low_memory=False, skiprows=1)

#Books
i_cols = ['isbn', 'book_title' ,'book_author','year_of_publication',␣
↪'publisher', 'img_s', 'img_m', 'img_l']
items = pd.read_csv('../BookReview/Data/BX-Books.csv', sep=';', names=i_cols,␣
↪encoding='latin-1',low_memory=False,skiprows=1)
```

```
#Ratings
r_cols = ['user_id', 'isbn', 'rating']
ratings = pd.read_csv('../BookReview/Data/BX-Book-Ratings.csv', sep=';',␣
↪names=r_cols, encoding='latin-1',low_memory=False,skiprows=1)
```

[3]:
```
users.head()
items.head()
ratings.head()
```

[3]:
```
   user_id        isbn  rating
0   276725  034545104X       0
1   276726  0155061224       5
2   276727  0446520802       0
3   276729  052165615X       3
4   276729  0521795028       6
```

merge the datasets

[4]:
```
df = pd.merge(users, ratings, on='user_id')
df = pd.merge(df, items, on='isbn')
df.head()
```

[4]:
```
   user_id                   location   age        isbn  rating  \
0        2  stockton, california, usa  18.0  0195153448       0
1        8   timmins, ontario, canada   NaN  0002005018       5
2    11400    ottawa, ontario, canada  49.0  0002005018       0
3    11676              n/a, n/a, n/a   NaN  0002005018       8
4    41385   sudbury, ontario, canada   NaN  0002005018       0

            book_title           book_author year_of_publication  \
0  Classical Mythology    Mark P. O. Morford                2002
1         Clara Callan  Richard Bruce Wright                2001
2         Clara Callan  Richard Bruce Wright                2001
3         Clara Callan  Richard Bruce Wright                2001
4         Clara Callan  Richard Bruce Wright                2001

                publisher                                              img_s  \
0  Oxford University Press  http://images.amazon.com/images/P/0195153448.0…
1    HarperFlamingo Canada  http://images.amazon.com/images/P/0002005018.0…
2    HarperFlamingo Canada  http://images.amazon.com/images/P/0002005018.0…
3    HarperFlamingo Canada  http://images.amazon.com/images/P/0002005018.0…
4    HarperFlamingo Canada  http://images.amazon.com/images/P/0002005018.0…

                                              img_m  \
0  http://images.amazon.com/images/P/0195153448.0…
1  http://images.amazon.com/images/P/0002005018.0…
```

```
2  http://images.amazon.com/images/P/0002005018.0…
3  http://images.amazon.com/images/P/0002005018.0…
4  http://images.amazon.com/images/P/0002005018.0…

                                                 img_l
0  http://images.amazon.com/images/P/0195153448.0…
1  http://images.amazon.com/images/P/0002005018.0…
2  http://images.amazon.com/images/P/0002005018.0…
3  http://images.amazon.com/images/P/0002005018.0…
4  http://images.amazon.com/images/P/0002005018.0…
```

0.1.3 2. Data description

[5]:
```
# dimension of the dataset
df.shape
```

[5]:
```
(1031175, 12)
```

[6]:
```
# number of users
df['user_id'].nunique()
```

[6]:
```
92107
```

[7]:
```
# number of books
df['isbn'].nunique()
```

[7]:
```
270170
```

[8]:
```
# summary statistics for numeric variables
df[['rating', 'age']].describe()
```

[8]:
```
              rating            age
count  1.031175e+06  753330.000000
mean   2.839022e+00      37.397719
std    3.854149e+00      14.098189
min    0.000000e+00       0.000000
25%    0.000000e+00      28.000000
50%    0.000000e+00      35.000000
75%    7.000000e+00      45.000000
max    1.000000e+01     244.000000
```

[9]:
```
# max age = 244, might be an error.
df.age[df['age'] <120].max()
```

[9]:
```
118.0
```

0.1.4 2.1 Explore the books and authors

[10]:
```
# number of books by year of publication (top ten years of most books published)
year_book = df.drop_duplicates(subset = ['year_of_publication',␣
↪'isbn'])[['year_of_publication', 'isbn']]
year_book.groupby(['year_of_publication'])['isbn'].count().
↪reset_index(name="Number of Books").sort_values(by = "Number of Books",␣
↪ascending=False).head(10)
```

[10]:

	year_of_publication	Number of Books
101	2002	17543
98	1999	17342
100	2001	17265
99	2000	17151
97	1998	15700
96	1997	14830
102	2003	14277
95	1996	13975
94	1995	13495
93	1994	11739

[11]:
```
# number of books by publisher
publisher_book = df.drop_duplicates(subset = ['publisher',␣
↪'isbn'])[['publisher', 'isbn']]
publisher_book.groupby(['publisher'])['isbn'].count().reset_index(name="Number␣
↪of Books").sort_values(by = "Number of Books", ascending=False).head(10)
```

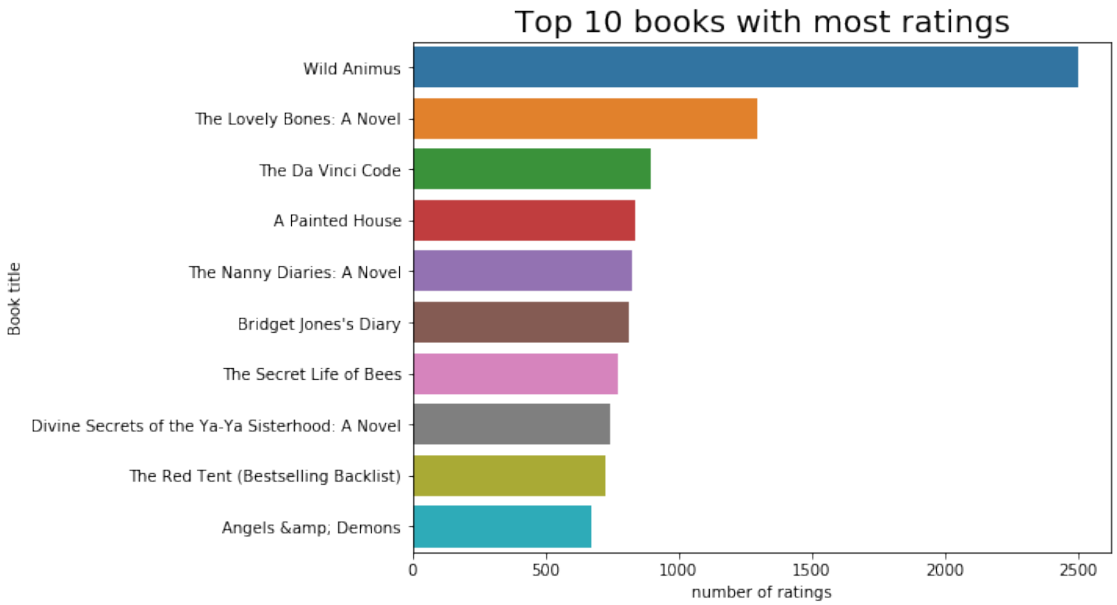
[11]:

	publisher	Number of Books
6574	Harlequin	7524
13624	Silhouette	4190
11727	Pocket	3896
1404	Ballantine Books	3775
1434	Bantam Books	3640
13220	Scholastic	3151
13669	Simon & Schuster	2965
11356	Penguin Books	2833
1730	Berkley Publishing Group	2764
15878	Warner Books	2720

[12]:
```
# Books with the most ratings
book_ratings = df.groupby(["book_title"])['user_id'].count().reset_index(name =␣
↪'number of ratings').sort_values(by = 'number of ratings', ascending = False)
Top10_book_ratings = book_ratings.head(10)

# draw a bar plot
plt.figure(figsize=(8,6))
sns.barplot(x='number of ratings',y='book_title',data=Top10_book_ratings)
```

```
plt.ylabel('Book title')
plt.title('Top 10 books with most ratings', size=20)
```

[12]:
```
Text(0.5, 1.0, 'Top 10 books with most ratings')
```



[13]:
```
# check the average number of ratings each book received: 3.82
# total number of ratings/total number of books
x = df.rating.count()
y = df.isbn.nunique()
x/y
```

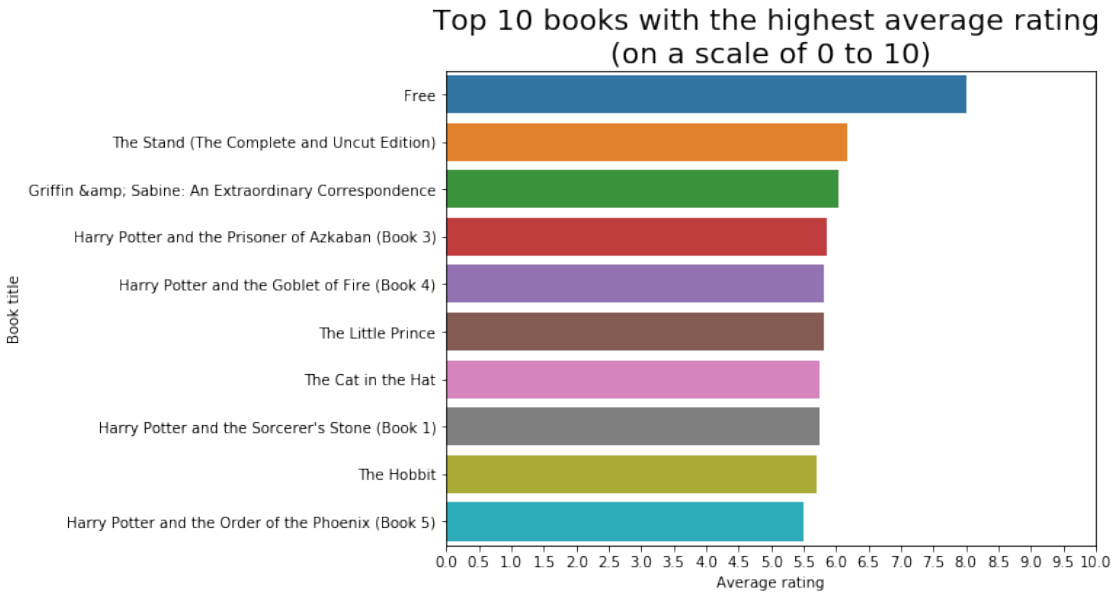
[13]:
```
3.8167635192656477
```

[14]:
```
# books with the highest average ratings.
book_ave_ratings = df.groupby('book_title').agg(count=('isbn', 'count'),␣
 ↪average_rating=('rating', 'mean')).reset_index()

# only focus on the books with at least 50 ratings
highest_rated_books = book_ave_ratings[book_ave_ratings['count'] >= 50].
 ↪sort_values(by = 'average_rating', ascending = False).head(10)
```

[15]:
```
# create a bar plot for the books with the highest average rating
plt.figure(figsize=(8,6))
sns.barplot(x='average_rating',y='book_title', data = highest_rated_books)
plt.ylabel('Book title')
plt.xlabel('Average rating')
plt.xticks(np.arange(0, 10.5, 0.5))
```

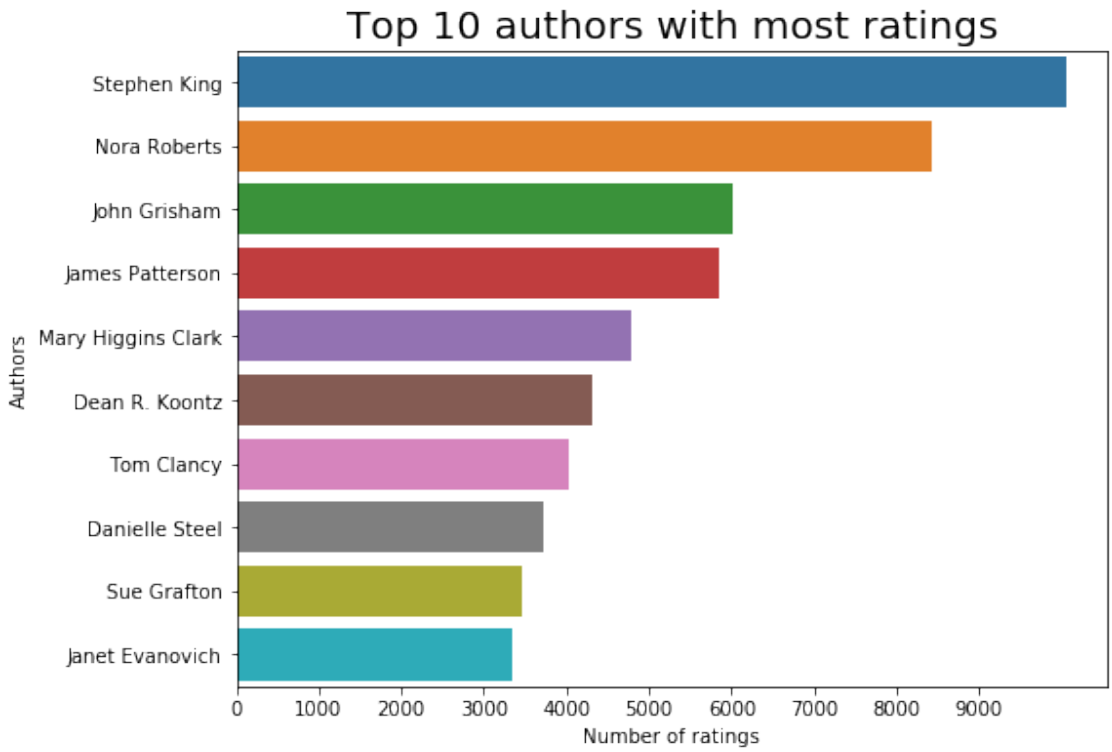
```
plt.title('Top 10 books with the highest average rating \n(on a scale of 0 to␣
 ↪10)', size=20)
```

[15]:
```
Text(0.5, 1.0, 'Top 10 books with the highest average rating \n(on a scale of 0
to 10)')
```



[16]:
```
# authors with most ratings
author_ratings = df.groupby(["book_author"])['user_id'].count().
 ↪reset_index(name = 'number of ratings').sort_values(by = 'number of ratings',␣
 ↪ascending = False)
top_author_ratings = author_ratings.head(10)

# plot a barchart for the top 10 authors with most ratings
plt.figure(figsize=(8,6))
sns.barplot(x='number of ratings',y='book_author', data = top_author_ratings)
plt.ylabel('Authors')
plt.xlabel('Number of ratings')
plt.xticks(np.arange(0, 10000, 1000))
plt.title('Top 10 authors with most ratings', size=20)
```

[16]:
```
Text(0.5, 1.0, 'Top 10 authors with most ratings')
```



[17]:
```
# creat a worldcloud for the famous authors (i.e. authors with most ratings)
!pip install wordcloud
from wordcloud import WordCloud,STOPWORDS
stop_words=set(STOPWORDS)

author_string = " ".join(df['book_author'].astype(str))
```

```
Requirement already satisfied: wordcloud in /opt/anaconda3/lib/python3.7/site-
packages (1.8.0)
Requirement already satisfied: numpy>=1.6.1 in
/opt/anaconda3/lib/python3.7/site-packages (from wordcloud) (1.18.1)
Requirement already satisfied: matplotlib in /opt/anaconda3/lib/python3.7/site-
packages (from wordcloud) (3.1.3)
Requirement already satisfied: pillow in /opt/anaconda3/lib/python3.7/site-
packages (from wordcloud) (7.0.0)
Requirement already satisfied: python-dateutil>=2.1 in
/opt/anaconda3/lib/python3.7/site-packages (from matplotlib->wordcloud) (2.8.1)
Requirement already satisfied: kiwisolver>=1.0.1 in
/opt/anaconda3/lib/python3.7/site-packages (from matplotlib->wordcloud) (1.1.0)
Requirement already satisfied: cycler>=0.10 in
/opt/anaconda3/lib/python3.7/site-packages (from matplotlib->wordcloud) (0.10.0)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in
/opt/anaconda3/lib/python3.7/site-packages (from matplotlib->wordcloud) (2.4.6)
```

```
Requirement already satisfied: six>=1.5 in /opt/anaconda3/lib/python3.7/site-
packages (from python-dateutil>=2.1->matplotlib->wordcloud) (1.14.0)
Requirement already satisfied: setuptools in /opt/anaconda3/lib/python3.7/site-
packages (from kiwisolver>=1.0.1->matplotlib->wordcloud) (46.0.0.post20200309)
```

[68]:
```
wc = WordCloud(width=600,height=400,␣
↪max_font_size=90,stopwords=stop_words,background_color='white').
↪generate(author_string)

fig=plt.figure(figsize=(8,6))
plt.axis('off')
plt.title('Wordcloud of Popular Authors',size=20)
plt.imshow(wc, interpolation='bilinear') # interpolation = 'bilinear' to make␣
↪the displayed image appear more smoothly
```

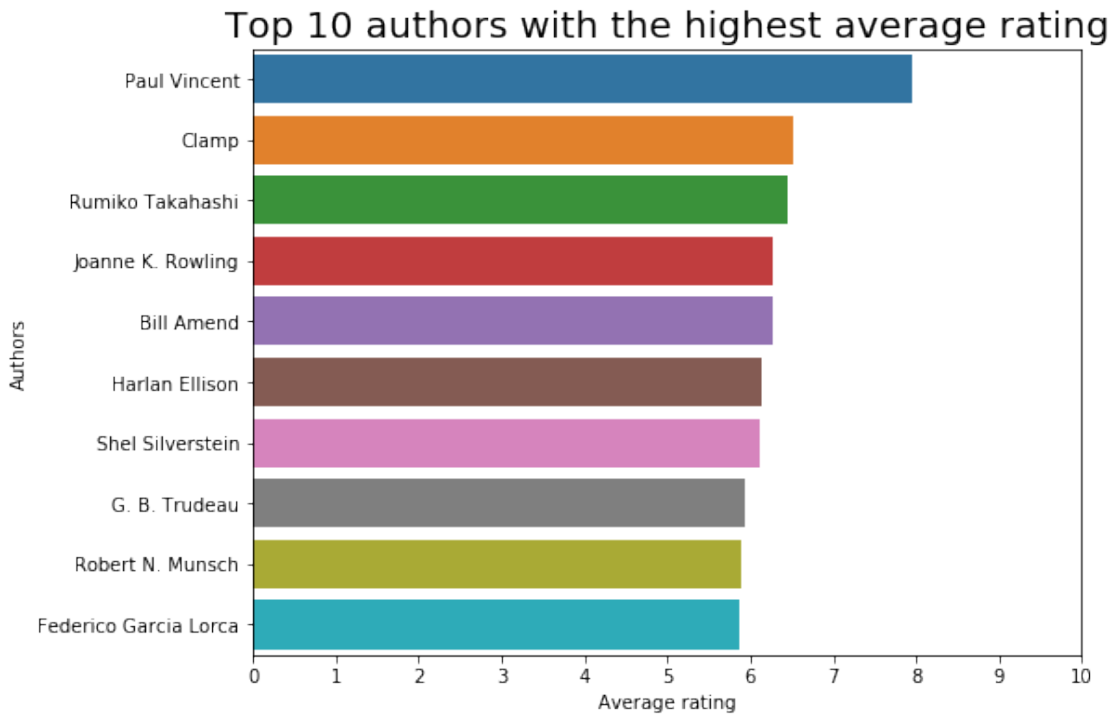
[68]:
```
<matplotlib.image.AxesImage at 0x1a4381ef90>
```

[62]:
```
# authors with the highest average rating.
author_rating = df.groupby('book_author').agg(count=('isbn', 'count'),␣
↪average_rating=('rating', 'mean')).reset_index()
```

```
# average number of ratings per author (aaverage number of ratings per author:␣
↪10.15)
author_rating['count'].mean()

# limited to authors with at least 50 ratings
top_author_rating = author_rating[author_rating['count'] >= 50].sort_values(by␣
↪= 'average_rating', ascending = False).head(10)
```

[20]:
```
# plot a bar chart for top 10 authors with the highest average rating
plt.figure(figsize=(8,6))
sns.barplot(x='average_rating',y='book_author', data = top_author_rating)
plt.ylabel('Authors')
plt.xlabel('Average rating')
plt.xticks(np.arange(0, 11, 1))
plt.title('Top 10 authors with the highest average rating', size=20)
```

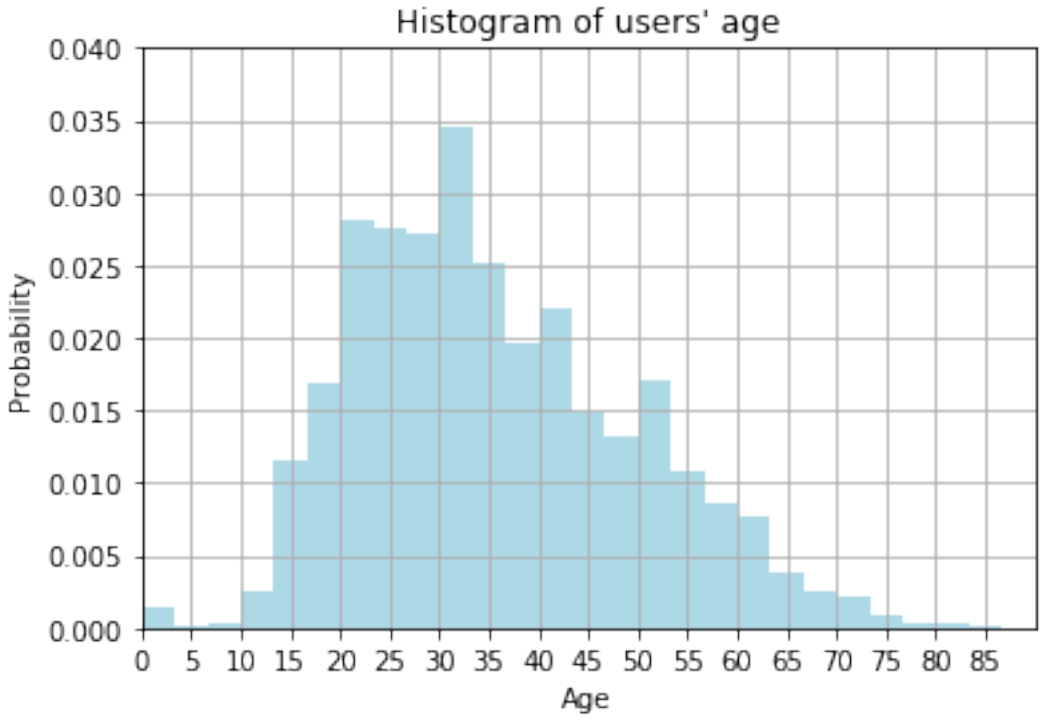
[20]:
```
Text(0.5, 1.0, 'Top 10 authors with the highest average rating')
```



0.1.5 2.2 Explore the users

[21]:
```
# the age distribution of the users
```

```
age_trunc = df[df['age'] <= 100]

# drop the duplicated users
age_trunc = age_trunc.drop_duplicates(subset = ['user_id'])['age']

# sns.distplot(age_trunc, bins=30, kde=True)

plt.hist(age_trunc, 30, density=True, facecolor='lightblue', alpha=1)
plt.xlabel('Age')
plt.ylabel('Probability')
plt.title('Histogram of users\' age')
plt.xlim(0,90)
x_ticks = np.arange(0, 90, 5)
plt.xticks(x_ticks)
plt.ylim(0, 0.04)
plt.grid(True)
plt.show()
```



[22]:
```
# the location (country) of the users

# split the location into city, state, and country
df[['city','state','country']] = df["location"].str.split(", ", expand=True,␣
 ↪n=2)
```

```
# drop the duplicated users
users = df.drop_duplicates(subset = ['user_id'])


country = users.groupby('country')['user_id'].count().reset_index(name =␣
↪'count')
```

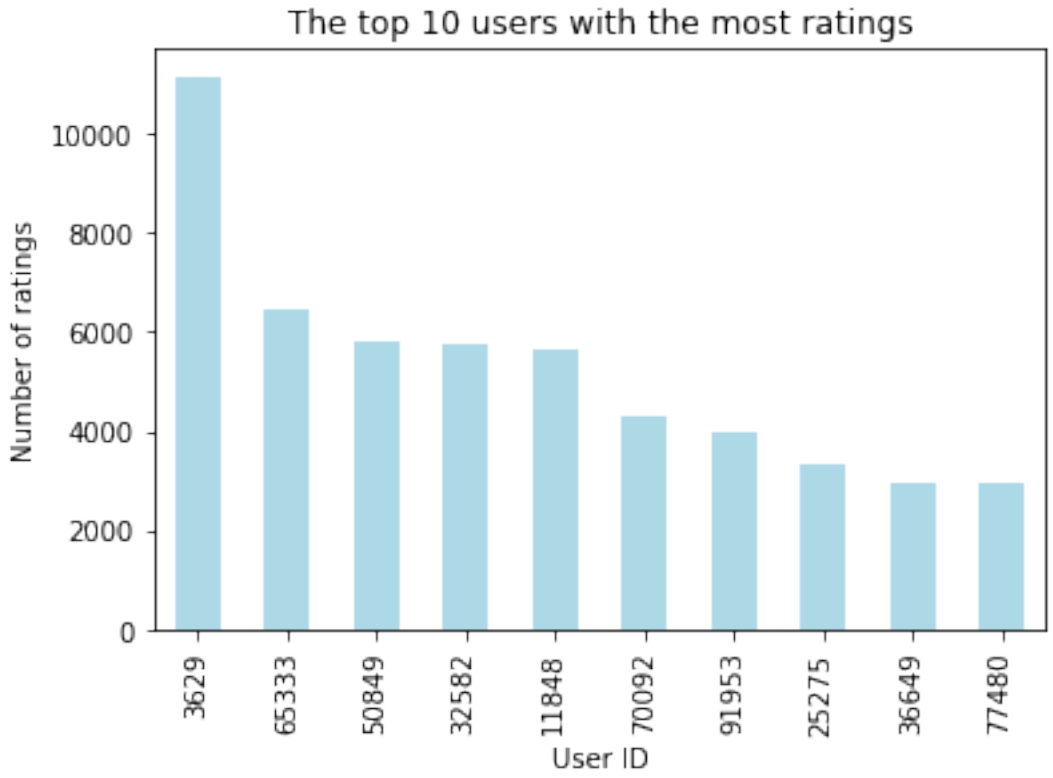
[23]:
```
# drop the countries with less than 1000 users
country2 = country[country['count'] >500 ]
```

[24]:
```
# plot a pie chart to show where do the users come from.
import plotly.express as px
fig = px.pie(country2,
             values="count",
             names="country",
             title="Home country of users",
             template="seaborn")
fig.update_traces(textposition="inside", textinfo="value+percent+label")
fig.show()
```

[25]:
```
# Where do the US users come from? (state)

US_users = users[users.country == "usa"]
state = US_users.groupby('state')['user_id'].count().reset_index(name = 'count')
state2 = state[state['count'] > 1500]

fig = px.pie(state2,
             values="count",
             names="state",
             title="Location (state) of the US users",
             template="seaborn")
fig.update_traces(textposition="inside", textinfo="value+percent+label")
fig.show()
```

[26]:
```
# Where do the US users come from? (city)

city = US_users.groupby('city')['user_id'].count().reset_index(name = 'count')
city2 = city[city['count'] > 250]

fig = px.pie(city2,
             values="count",
             names="city",
             title="Location(city) of the US users",
             template="seaborn")
fig.update_traces(textposition="inside", textinfo="value+percent+label")
fig.show()
```

[27]:
```
# The top 10 users with the most ratings.
user_rating = df.groupby('user_id')['user_id'].count().reset_index(name =␣
↪'number of ratings').sort_values(by = 'number of ratings', ascending = False)
top10_users = user_rating.head(10)

# plot a bar chart
top10_users['number of ratings'].plot.bar(x='User ID', y='Number of ratings',␣
↪color = 'lightblue')

# Add title and axis names
plt.title('The top 10 users with the most ratings')
plt.xlabel('User ID')
plt.ylabel('Number of ratings')
plt.show()
```



0.1.6 3. Book recommender

0.1.7 3.1 Collaborative Filtering (item-based)

0.1.8 Data Processing

[28]:
```
mydf = df[['user_id', 'book_title', 'rating']]

# drop duplicates
mydf = mydf.drop_duplicates(subset = ['user_id', 'book_title'])

# I consider 'rating = 0' as a valid rating
# 382,203 observations with rating > 0
# 644,194 observations with rating = 0
```

To get an idea about a user's preference, we need a user who's rated at least 5 books. Similarly, to derive predictions regarding book recommendations, we need books that have been rated at least 5 times.

[29]:
```
# restrict to books with at least five ratings (quality books)
books = mydf['book_title'].value_counts().rename_axis('book_title').
 ↪reset_index(name = 'count')
books = books[books['count']>5]['book_title'].to_list()
quality_rating = mydf[mydf['book_title'].isin(books)]
```

[30]:
```
# restric to users with at least 5 ratings (quality users)
users = mydf['user_id'].value_counts().rename_axis('user_id').reset_index(name␣
 ↪= 'count')
users = users[users['count']>5]['user_id'].to_list()
quality_rating = quality_rating[quality_rating['user_id'].isin(users)]
```

[31]:
```
quality_rating.head()
# No. of observations reduced from 1,026,397 to 585,687
```

[31]:

	user_id	book_title	rating
1	8	Clara Callan	5
2	11400	Clara Callan	0
3	11676	Clara Callan	8
4	41385	Clara Callan	0
5	67544	Clara Callan	8

[32]:
```
# there is no missing value
quality_rating.isnull().sum()
```

[32]:
```
user_id       0
book_title    0
rating        0
dtype: int64
```

Some users may be tougher than the others, that is, they tend to always give ratings lower than the average. So we need to bring all users to the same level by removing their bias. I subtract the average rating given by each user to all books from each book rated by that user (i.e. demeaning). By doing this, we have changed the value of average rating given by every user to 0, which brings them all to the same level and remove their bias.

[33]:
```
# demeaning the data

quality_rating['trans_rating'] = quality_rating['rating'] - quality_rating.
 ↪groupby('user_id')['rating'].transform('mean')
```

When converting to pivot table, we are working with an extremely sparse matrix. We fill the missing values with 0.

[34]:
```
# pivot table
book_ratings = pd.pivot_table(quality_rating, index = 'book_title', columns =␣
 ↪'user_id', values = 'trans_rating', fill_value=0)
```

A lot of values in the pivot table are zero. Thus, we're dealing with extremely sparse data. In such a case, we need to work with a scipy-sparse matrix to avoid overflow and wasted memory.

[ ]:
```
# transform to scipy-sparse matrix

from scipy.sparse import csr_matrix
book_ratings_sparse = csr_matrix(book_ratings)
```

0.1.9 Applying the KNN Algorithm

[50]:
```
from sklearn.neighbors import NearestNeighbors

#make an object for the NearestNeighbors Class.
model_knn = NearestNeighbors(metric='cosine', algorithm='brute',␣
 ↪n_neighbors=10, n_jobs=-1)

# fit the dataset
model_knn.fit(book_ratings_sparse)
#distances, indices = model_knn.kneighbors(book_ratings_sparse)
```

[50]:
```
NearestNeighbors(algorithm='brute', leaf_size=30, metric='cosine',
                 metric_params=None, n_jobs=-1, n_neighbors=10, p=2,
                 radius=1.0)
```

0.1.10 Making recommendations

[51]:
```
# get the list of book titles
book_titles = book_ratings.index.to_list()

# get the cover image of the books
book_cover = items[items['book_title'].isin(books)]['img_m']

# valid book titles
```

```
titles = quality_rating.drop_duplicates(subset = 'book_title')

# all books with images in the original book data
all_books = items.drop_duplicates(subset = 'book_title')

# merge with the original book data
merged_book = pd.merge(all_books, titles, on = 'book_title', how='right')

merged_book = merged_book.sort_values(by = 'book_title')
```

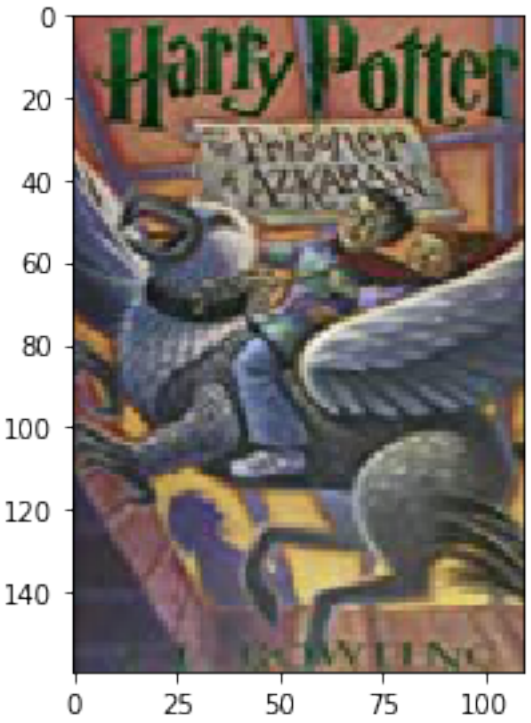
[69]:
```
from IPython.display import Image
from skimage import io


def make_recommendation(model_knn, data, fav_book, n_recommendations):

    # fit the model
    model_knn.fit(data)

    query_index = book_titles.index(fav_book)

    distances, indices = model_knn.kneighbors(data[query_index],␣
 ↪n_neighbors=n_recommendations+1)

    raw_recommends = sorted(list(zip(indices.squeeze().tolist(), distances.
 ↪squeeze().tolist())), key=lambda x: x[1])[1:]


    print('You have input book:', fav_book)
    print('Recommendation system starts to make inference')
    print('......\n')

    print('Recommendations for {}:'.format(fav_book))
    for i, (idx, dist) in enumerate(raw_recommends):
        #url = merged_book.iloc[idx]['img_m']

        print('{0}: {1}'.format(i+1, book_titles[idx]))
        #print('{0}: {1}, with distance of {2}'.format(i+1, book_titles[idx],␣
 ↪dist))
        #io.imshow(io.imread(url))
        #io.show()
```

[73]:
```
# Example 1
my_book = 'The Little Prince'
make_recommendation(model_knn, book_ratings_sparse, my_book, 5)
```

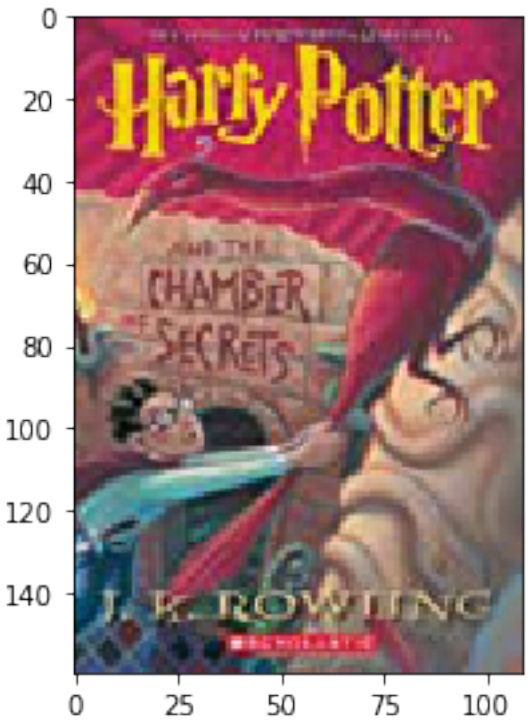
```
You have input book: The Little Prince
Recommendation system starts to make inference
…

Recommendations for The Little Prince:
1: Life Strategies for Teens
2: Just Between Us . . .   Kiss &amp;amp; Tell (Harlequin Blaze)
3: The Birds and the Bees
4: Baby Doctor  (Emergency) (Harlequin Superromance, No 753)
5: In Name Only (Texas Grooms) (Desire, 1313)
```

[59]:
```
# Example 2
my_book = 'Harry Potter and the Goblet of Fire (Book 4)'
make_recommendation(model_knn, book_ratings_sparse, my_book, 5)
```

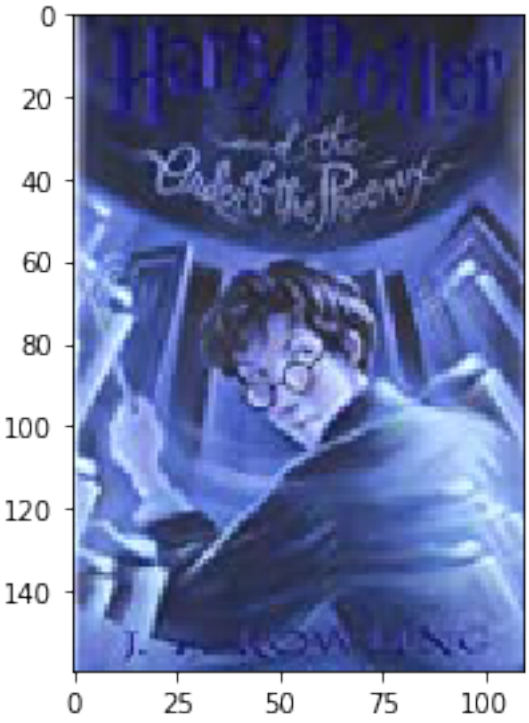
```
You have input book: Harry Potter and the Goblet of Fire (Book 4)
Recommendation system starts to make inference
…

Recommendations for Harry Potter and the Goblet of Fire (Book 4):
1: Harry Potter and the Prisoner of Azkaban (Book 3), with distance of
0.5502615797063404
```



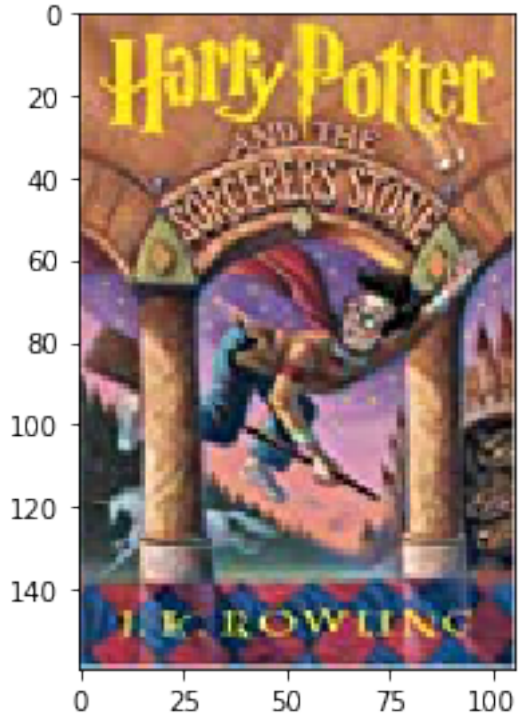
2: Harry Potter and the Chamber of Secrets (Book 2), with distance of 0.6321323360572636



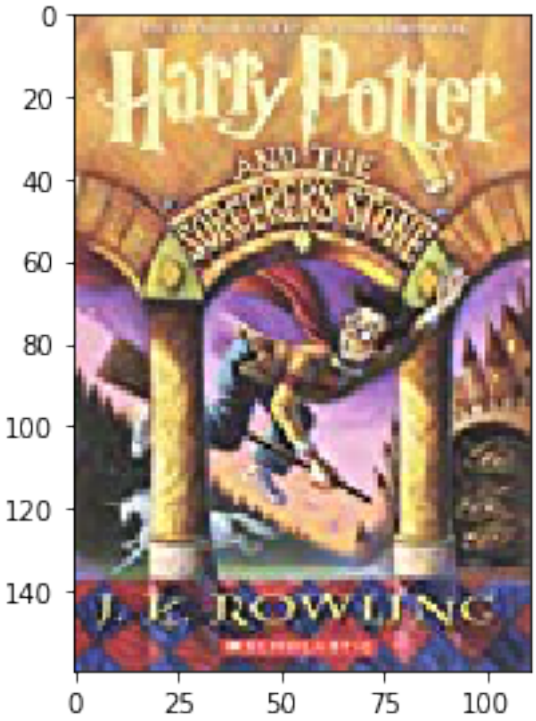
3: Harry Potter and the Order of the Phoenix (Book 5), with distance of 0.6968846897538532



4: Harry Potter and the Sorcerer's Stone (Book 1), with distance of 0.7281455899104569



```
5: Harry Potter and the Sorcerer's Stone (Harry Potter (Paperback)), with
distance of 0.8464401445895224
```



0.1.11 3.2 Content-based Filtering

We do not have detailed information about the content of the books, such as genre, or content description. The only information we might use is the title of the books.

0.1.12 Creating a TF-IDF vectorizer

[60]:
```
from sklearn.feature_extraction.text import TfidfVectorizer
```

[ ]:
```
titles = merged_book['book_title']
vectorizer = TfidfVectorizer(analyzer='word',  stop_words='english')
tfidf_matrix = vectorizer.fit_transform(titles)

tfidf_matrix.shape  # 31,630 books with 19,263 words in the titles (bag of words)
```

The tfidf_matrix is the matrix containing each word and its TF-IDF score with regard to each book title. Also, stop words are simply words that add no significant value to our system, like 'an',

'is', 'the', and hence are ignored by the system. Now, we have a representation of every book in terms of the words of the titles. Next, we need to calculate the relevance or similarity of one book to another.

0.1.13 Calculating Cosine similarity

[ ]:
```
from sklearn.metrics.pairwise import linear_kernel

cosine_similarities = linear_kernel(tfidf_matrix, tfidf_matrix)
cosine_similarities.shape
```

[ ]:
```
cosine_similarities[0] # the first row
```

[ ]:
```
results = {}
for idx, row in ds.iterrows():
    similar_indices = cosine_similarities[idx].argsort()[:-100:-1]
    similar_items = [(cosine_similarities[idx][i], ds['id'][i]) for i in␣
 ↪similar_indices]
    results[row['id']] = similar_items[1:]
```

[ ]:
```
# vectorizer = TfidfVectorizer(analyzer='word', ngram_range=(1, 1), min_df=0,␣
 ↪stop_words='english')
# vectors = vectorizer.fit_transform(corpus)
# feature_names = vectorizer.get_feature_names()
# dense = vectors.todense()
# denselist = dense.tolist()
# df = pd.DataFrame(denselist, columns=feature_names)
# df
```

[ ]:

[ ]:

[ ]: