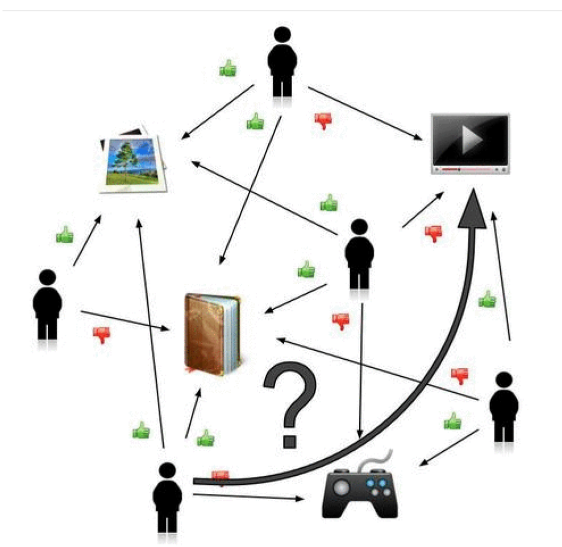
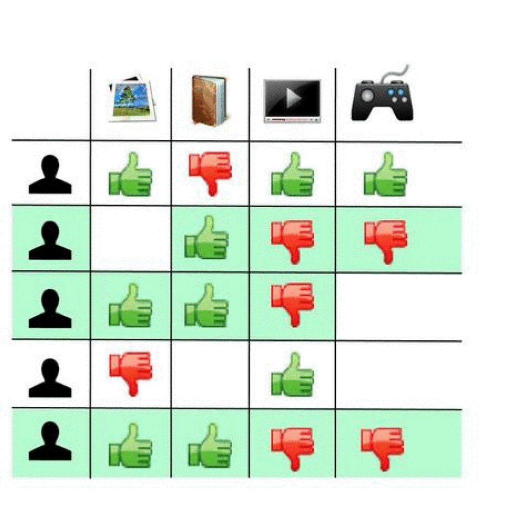
Final Report

"Capstone Project 2 : Book bundles recommendation from book readers ratings and book sales data"

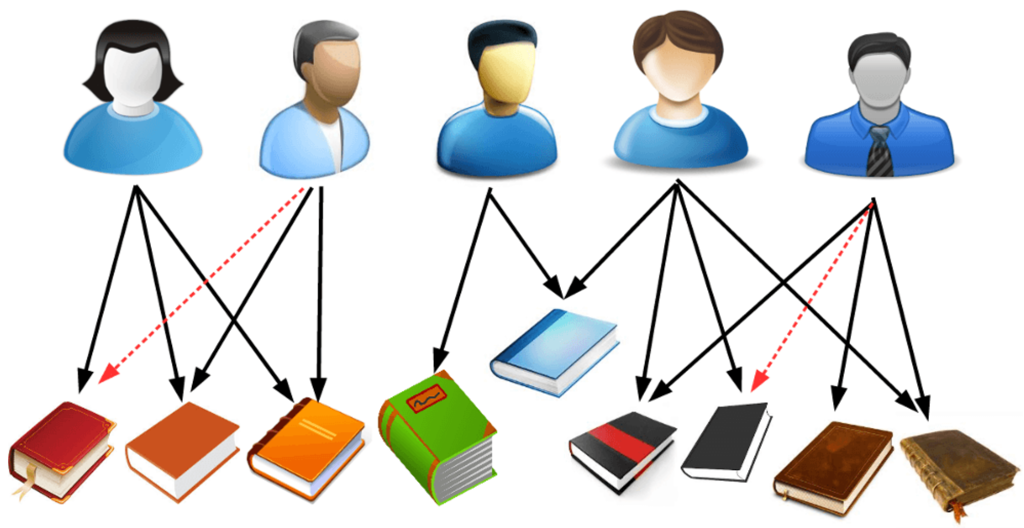
INTRODUCTION

A recommendation system is a type of information filtering system that predicts the rating or preference that a user would give to an item. Recommendation systems are targeted to individuals who do not have enough personal experience to evaluate the potentially overwhelming alternatives that a web site, for instance, may offer. They aim at presenting relevant information and reducing the information overload so that it is likely to interest the user.





This analysis aims to recommend book bundles to the readers from book ratings and book sales data. We all had an online experience where a website makes some personalized recommendations. Youtube tells you "...viewers also watch...", Amazon tells you, “Customers Who Bought This Item Also Bought,” and Udemy tells you, “Students Who Viewed This Course Also Viewed.” A recommender system is a simple algorithm whose aim is to provide the most relevant information to a user by discovering patterns in a dataset. The algorithm rates the items and shows the user the things that they would rate highly.



The recommendation system can be deployed as a web app where people can use to get recommendations based on reading history. Schools can use the system to increase students learning interest, adapts to student needs, moving at a slower or faster pace to help students with different strengths and learning styles to reach their full potential. Online book stores can offer book bundles to their customers.

Data collection

The data can be collected by two means: explicitly and implicitly. I used explicit data that is provided intentionally by the users as a rating. I checked different datasets like Cai-Nicolas Ziegler's Book-Crossings dataset; Julian McAuley's Amazon product dataset, Open library book dataset, Worldcat book dataset, Goodreaders dataset. I used the updated Goodreaders dataset in my project.

Before concatenating tables, all datasets are diagnosed for the inconsistent column names, missing data, duplicate rows, untidy, and unexpected data values. All datasets were explored with pandas methods such as .head(), .info(), and .describe(), and DataFrame attributes like .columns and .shape . Needed datasets are concatenated, and a single dataframe is created and saved for later analysis.

The data consists of three tables: ratings, books info, and user info.

The books data set provides book details. It includes 10000 records and 24 fields: book id, Goodreads book id, best book id, work id, books count, ISBN, ISBN13, authors, original publication year, original title, title, language code, average rating, ratings count, work ratings count, worktext reviews count, ratings 1, ratings 2, ratings 3, ratings 4, ratings 5, image URL, and small image URL.

The rating data set provides a list of ratings that users have given to books. It includes 5976479 records and three fields: user id, book id, and rank. The users' data dataset provides the user demographic information. It contains 912705 records and two fields: user id, and book id.

The datasets have missing data and duplicate rows. I filled the null rating data with “0”. I checked the sparsity level of the dataset to see the percentage of cells that are not populated and populated, respectively. Some changes might have to be made, but for now, this is the first draft of the dataframe. This cleaned dataframe is saved for further analysis.

Exploratory Data Analysis

As seen in the below table over we are missing many books ISBN. ISBN is a unique number, and I won’t be able to use it as a reference. I won’t be able to fill it with O or median value as well. Our data has negative publication years, missing data, and old dates. I investigate those books. Negative values filled with the median and left old dates in the database.

```python
# See the column data types and non-missing values
books.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 23 columns):
book_id                      10000 non-null int64
goodreads_book_id            10000 non-null int64
best_book_id                 10000 non-null int64
work_id                      10000 non-null int64
books_count                  10000 non-null int64
isbn                         9300 non-null object
isbn13                       9415 non-null float64
authors                      10000 non-null object
original_publication_year    9979 non-null float64
original_title               9415 non-null object
title                        10000 non-null object
language_code                8916 non-null object
average_rating               10000 non-null float64
ratings_count                10000 non-null int64
work_ratings_count           10000 non-null int64
work_text_reviews_count      10000 non-null int64
ratings_1                    10000 non-null int64
ratings_2                    10000 non-null int64
ratings_3                    10000 non-null int64
ratings_4                    10000 non-null int64
ratings_5                    10000 non-null int64
image_url                    10000 non-null object
small_image_url              10000 non-null object
dtypes: float64(3), int64(13), object(7)
memory usage: 1.8+ MB
```

In [8]:
```python
#missing values in 'original_publication_year'
books.original_publication_year.unique()
```

```
             1891.,  1897.,  1963.,  1844.,  2013.,  1862.,  1961.,  1876.,
             1962.,  1955.,  1991.,  1600.,  1965.,  1939.,  1908.,  1850.,
             2014.,  1606.,  1860.,  1942.,  1978.,  1815.,  1877.,  1986.,
             1866.,  1922.,  1987.,  1851.,  1982.,  1843.,  1976.,  1994.,
             1915.,  1956.,    nan,  1980.,  1865.,  1817.,  1957.,  1926.,
             1943.,  1938.,  1966.,  1981.,  2016.,  1992.,  1984.,  1972.,
             1882.,  1895.,  1899.,  1983.,  -750.,  1900.,  1975.,  1971.,
             1603.,  1929.,  1968.,  1838.,  1903.,  1886.,  1940.,  -500.,
             1887.,  1931.,  1611.,  1814.,  1719.,  1513.,  1880.,  1923.,
             1869.,  1849.,  1892.,  1904.,  1726.,  1598.,   975.,  1905.,
             1935.,  1948.,  1856.,  1759.,  1959.,  1605.,  1901.,  1970.,
             1902.,  1390.,  1852.,  1909.,  1920.,  1934.,  1872.,  1894.,
             1599.,  -380.,  1593.,  1831.,  1812.,  1623.,  1854.,  -430.,
             1596.,  1601.,  1941.,  1906.,  1930.,  1916.,  1871.,  1864.,
             1320.,  1667.,  1927.,  1874.,  1918.,  -300.,  1835.,  1883.,
             -560.,  1914.,  1308.,  1881.,  1933.,   -17.,  1830.,  1678.,
             1848.,  1826.,  1912.,  1853.,  1890.,  -441.,  1928.,  1896.,
             1879.,  1819.,  1889.,  1592.,  1855.,  1845.,  1924.,  1944.,
             1898.,   800.,  1910.,   180.,  -401., -1750.,   609.,  1919.,
             -762.,  1842.,  1774.,  1808.,  -400.,  1861.,  1846.,     8.,
```

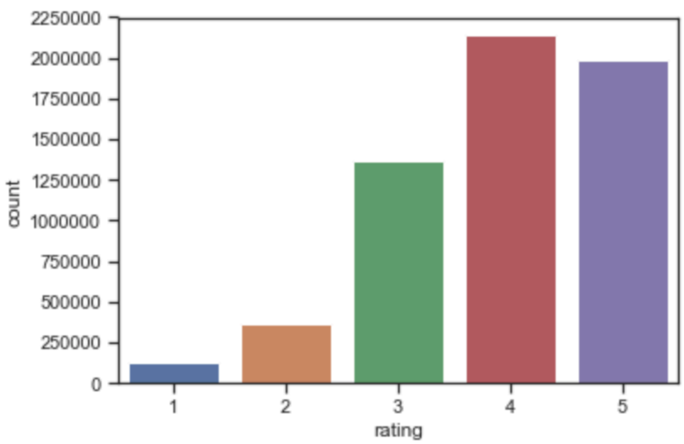
We have 10000 books and 912705 users. The sparsity level of our Book dataset is 99.9 %.

```
In [27]: print ("number of users: " + str(n_users))
         print ("number of books: " + str(n_books))

number of users: 912705
number of books: 10000
```

```
In [28]: #Sparsity of dataset in %
         sparsity=1.0-len(ratings_new)/float(n_users*n_books)
         print ('The sparsity level of Book dataset is ' +  str(sparsity*100) + ' %')

The sparsity level of Book dataset is 99.93451905051468 %
```

The number of books that are rated 1-5.

```
#plotting count of rating
sns.countplot(data=ratings_explicit , x='rating')
plt.show()
```



I combined ratings and book datasets and drop columns that I won't use in my recommendation. A new dataset has 5975161 rows and 11 columns.

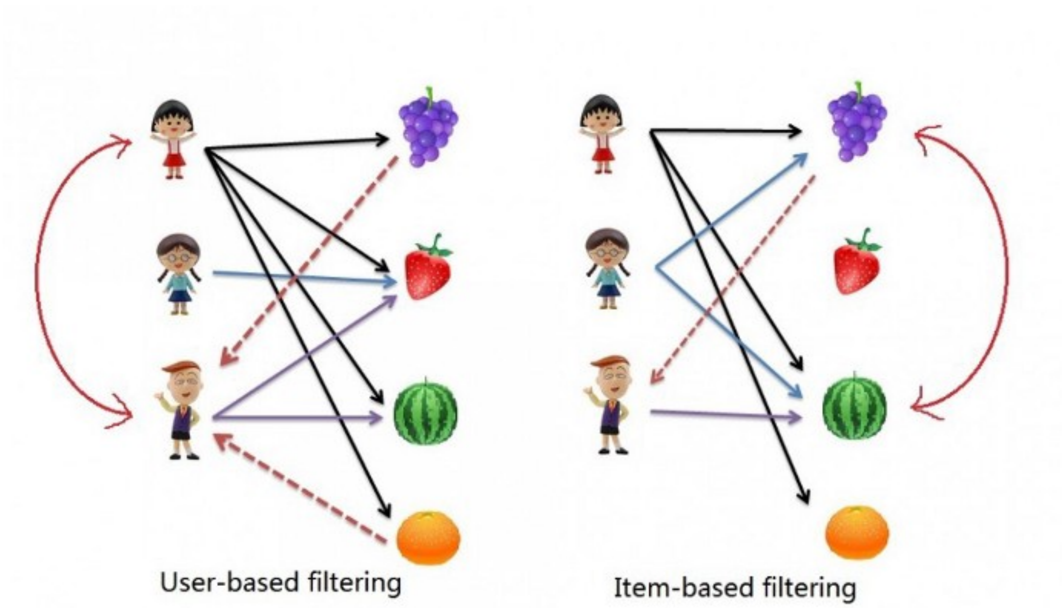
```
In [33]: if not combine_book_rating[combine_book_rating.duplicated(['user_id', 'title'])].empty:
             initial_rows = combine_book_rating.shape[0]

             print('Initial dataframe shape {0}'.format(combine_book_rating.shape))
             combine_book_rating = combine_book_rating.drop_duplicates(['user_id', 'title'])
             current_rows = combine_book_rating.shape[0]
             print('New dataframe shape {0}'.format(combine_book_rating.shape))
             print('Removed {0} rows'.format(initial_rows - current_rows))

Initial dataframe shape (5976479, 11)
New dataframe shape (5975161, 11)
Removed 1318 rows
```

The mean average rating is 4.02, and 1% of books have 4.54 ratings, 2% have 4.52 ratings.

```
n [35]: print(combine_book_rating['average_rating'].quantile(np.arange(.9, 1, .01)))

        0.900    4.330
        0.910    4.340
        0.920    4.350
        0.930    4.370
        0.940    4.390
        0.950    4.420
        0.960    4.440
        0.970    4.460
        0.980    4.520
        0.990    4.540
        Name: average_rating, dtype: float64
```

Recommendation system

I used the nearest-neighbor model of collaborative filtering. The collaborative filtering approach builds a model from a user's past behaviors like items previously purchased or selected and/or numerical ratings given to those items as well as similar decisions made by other users. This model is then used to predict things (or ratings for items) that the user may have an interest in. To implement item-based collaborative filtering, KNN is a perfect go-to model and also an ideal baseline for recommender system development. KNN does not make any assumptions on the underlying data distribution, but it relies on item feature similarity. When KNN makes inference about a book, KNN will calculate the "distance" between the target book and every other book in its database. It ranks its distances and returns the top K nearest neighbor books as the most similar book's recommendations.



As seen below, the book recommendation system is calculating the distance between the book and similar books. It recommends the nearest five books.

```
Recommendations for Brain Rules: 12 Principles for Surviving and Thriving at Work, Home, and School:

1: A Whole New Mind: Why Right-Brainers Will Rule the Future, with distance of 0.84546381728754433:

2: How We Decide, with distance of 0.86039800432408006:

3: Drive: The Surprising Truth About What Motivates Us, with distance of 0.86294234472043392:

4: Talent is Overrated: What Really Separates World-Class Performers from Everybody Else, with distance of 0.86510736
96099224:

5: The Upside of Irrationality: The Unexpected Benefits of Defying Logic at Work and at Home, with distance of 0.8722
994549069018:

Perfect! This books are definitely should be recommended one after another
```

Conclusion

This capstone project has taught me just machine learning techniques are not enough to build a recommendation system, practical computer issues. The right research coding questions are also a great deal to solve the problem.

A collaborative filtering system does not necessarily succeed in automatically matching content to one's preferences. It requires a substantial number of users to rate a new item before that item can be recommended. A lack of insufficient data entry might cause collaborative filtering not to work accurately. An area for improvement of the model would be to collect data from different book sites weekly and to compare ratings for accuracy. People may also give lots of positive ratings for their items and negative ratings for their competitors. A security algorithm is necessary for such kinds of manipulations.

Another issue might be the new users and new items in the system. New users will need to rate the sufficient number of items to enable the system to capture their preferences accurately and thus provides reliable recommendations. Similarly, new items need to be rated by a substantial amount of users before they could be recommended to users who have similar tastes to the ones who rated them. Most recommender systems are unable to discover the tendency of a number of the same or very similar items to have different names or entries. This will decreases the recommendation performance of the system. Another suggestion to improve recommendation is the topic modeling that could solve this problem by different grouping words belonging to the same topic.

References

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