NLP Book Recommendation System

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Problem Definition

- Finding the next perfect book has always been a challenge for book lovers. With the large number of books being published every year, the task of finding just the right book a particular reader will like becomes more and more difficult. If booksellers can recommend the right books for readers, they can boost their revenue tremendously.
- The purpose of this project is to identify which books are similar based on text analysis of categories and descriptions of the books. The system will take a title of a book that the user read before and liked as an input. Then it will recommend the 5 most similar books to the chosen title.

Dataset

- I used the Amazon Book Reviews data available on Kaggle here: https://www.kaggle.com/datasets/mohamedbakhet/amazon-books-reviews?select=books_data.csv
- This is a rich dataset for Natural Language Processing containing text descriptions and categories for 212,403 books as well as 3,000,000 text reviews from users. Therefore it is ideal for text analysis.
- The data originally come in two csv files, one for books data and the other for user reviews data, with the below columns.
- Books: Title, description, authors, image, previewLink, publisher, publishedDate, infoLink, categories, ratingsCount
- Ratings: Id, Title, Price, User_id, profileName, review/helpfulness, review/score, review/time, review/summary, review/text

Data Cleaning - Missing Values

Title	1
review/score_Avg	1
review/score_Count	1
description	68442
authors	31413
publishedDate	25622
categories	41199
dtype: int64	

- Published date: filled the missing dates with the average published date value.
- Authors: filled missing values with ‘unknown’
- Description and categories: Since these columns are vital for text analysis, I dropped the rows with null description or categories.
- Title, review/score_avg, and review/score_count - removed the missing rows.

Additional Data Cleaning Tasks Performed

Major data cleaning tasks performed.

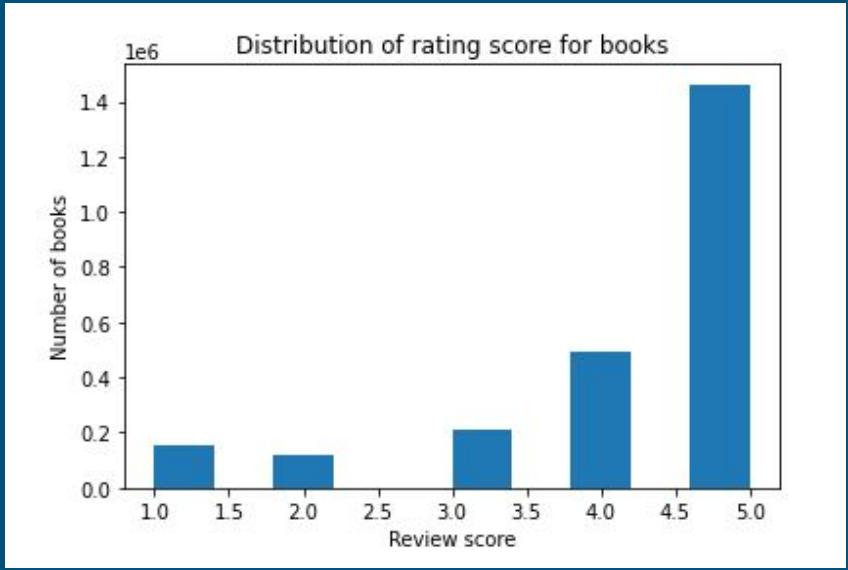
- Dropped unneeded columns from the books data and the ratings data.
- Categories column
  - has 5415 unique categories.
  - It has duplicate categories with slightly different wording. I left it as is because I planned to perform NLP processes on this column which would detect similar categories as similar to each other.
- Title column - some duplicate titles with slightly different wording/spelling and/or case.
  - Converted to lowercase and removed duplicates. Dropped the duplicates with less number of ratings and kept the ones with the highest number of ratings.
  - Still some duplicate titles with slightly different wording/spellings remained.
- I removed empty spaces, special characters and numbers from the Title column.

Exploratory Data Analysis - Authors with the Highest Total Number of Reviews for All Their Books

authors	Total # of Reviews
['J. R. R. Tolkien']	37268.0
['Jane Austen']	29933.0
['Charles Dickens']	17690.0
['John Steinbeck']	15461.0
['John Ronald Reuel Tolkien']	12558.0
['Kurt Vonnegut']	12093.0
['Harper Lee']	12013.0
['C. S. Lewis']	11800.0
['F. Scott Fitzgerald']	10535.0
['George Orwell']	10182.0

Name: review/score_Count, dtype: float64

Exploratory Data Analysis
Ratings



- Most ratings are 4 or 5 points.
- Most users rated between 1 to 5 books. However, the highest number of ratings by one user is 5795 and the second highest is 3606. I quickly scanned these ratings and they looked genuine.

Exploratory Data Analysis - Books with Higher Number of Reviews Received Lower Average Rating

- Books which received higher number of ratings had lower average ratings than the average rating for all the books.
- When a book has a large number of ratings, it is likely to have some of the lower ratings.

	Mean Rating	**Median Rating**
Books With >10 Reviews	4.21	4.30
All Books	4.26	4.48

Feature Engineering and Text Preprocessing

- Calculated the average review score and the total number of ratings for each book and columns added to the Books data.
- Converted the publishedDate column in the books data to date/time in the format of 4-digit year.
- Combined the categories and description columns and created a description_categories column. This column was used for NLP processes to produce the book recommendations.
- Removed special characters and numbers from the description_categories and converted text to lower.
- Tokenized the text in the description_categories column to separate each word in the text using word_tokenize from nltk library.
- Lemmatized each word using WordNetLemmatizer from the nltk library to reduce variant forms of words to one word.
- Removed stop words (the, and, are, is …) using the nltk.corpus to generate stop words list.
- I joined the words back together to form one long string for the categories_description value of each book.
- Finally , I took a subset of the data (books with >10 ratings, about 30,000 books) for the modeling.

Making the Recommendations

- Built three models that make the book recommendations and compared their performance.
- The models take a book title that the user read and liked as an input. The system then looks for five books that are most similar to that chosen title and make recommendations.

Model 1 - CountVectorizer and Cosine Similarity

Steps taken:

1. Used CountVectorizer from the Scikit Learn library to create vectors for the description_categories text.
2. Created the Cosine Similarity matrix for the whole data using Scikit Learn's Cosine Similarity function.
3. Took the row for the chosen title in the matrix. From that row, the 5 highest similarity score values correspond with the books that are most similar to the chosen title.

Model 2 - Spacy

Here are the steps I took to make book recommendations with this model:

1. Vectorized the description_categories column using nlp.
2. Computed the similarity score of the chosen book with all of the books, including itself using Spacy.
3. Sorted the similarity scores in descending order to find the 5 most similar books to the chosen book.
4. The system computes similarity scores of a chosen title when needed instead of calculating similarity scores of the whole data in advance. With this model, this step runs fast and doesn't negatively affect the speed of the model.

Model 3 - with SBERT Sentence Transformer and Cosine Similarity

Steps taken:

1. Created sentence embeddings for the description_categories column using SBERT SentenceTransformer.
2. Created the cosine similarity matrix based on the sentence embeddings using the cos_sim function in the SBERT library.
3. After that, I was able to pick the row for the chosen title in the matrix using its index value. I then sorted that row and take the top 5 books with the highest similarity scores with the chosen book.
4. Creating the sentence embeddings and similarity matrix takes some time to run. However, once the matrix is created, making recommendations is very fast.

Choosing Model 1, Model 2 or Model 3?

Chosen model - SBERT Sentence Transformer pretrained model (Model 3)

1. The Spacy model (Model 2) - simpler model, runs fast, but seems to produce lower quality recommendations.
2. Count Vectorizer and Cosine Similarity model (Model 1). The model takes a while to run, but produces decent recommendations.
3. SBERT Sentence Transformer model (Model 3) The model doesn't take too long to run and seems to produce the best quality recommendations.
4. SBERT Model takes into consideration the semantic and contextual meanings of words and sentences.
5. In all I am impressed with how all of the models were able to analyze text information and pick out similar books out of thousands of books.

How About Accuracy Matrix?

- Used Discounted Cumulative Gains (DCG) to measure and compare performances of the three models. Accuracy comparison table in the next slide.
- Manually compared description of chosen titles and recommended titles to determine relevancy score.
- DCG = Relevancy Score/(LOG(Recommendation Rank+1))
- Formula Source: Towards Data Science, An Exhaustive List of Methods to Evaluate Recommender Systems

Accuracy Measure: Discounted Cumulative Gains (DCG)

Scoring Key:

Most relevant => 2

Somewhat relevant => 1

Least relevant => 0

		Count Vectorizer	Count Vectorizer	Gensim / Spacy	Gensim / Spacy	SBERT	SBERT
Chosen Book Title	Recomm-endation Rank	Relevancy Score (CG)	DCG	Relevancy Score (CG)	DCG	Relevancy Score (CG)	DCG
1 is one	1	2	6.64	2	6.64	2	6.64
	2	2	4.19	2	4.19	2	4.19
	3	2	3.32	0	0.00	2	3.32
	4	2	2.86	0	0.00	2	2.86
	5	2	2.57	2	2.57	2	2.57
spanish stepbystep	1	2	6.64	1	3.32	2	6.64
	2	1	2.10	1	2.10	2	4.19
	3	2	3.32	1	1.66	1	1.66
	4	2	2.86	1	1.43	1	1.43
	5	1	1.29	1	1.29	1	1.29
to kill a mockingbird	1	2	6.64	2	6.64	2	6.64
	2	1	2.10	2	4.19	2	4.19
	3	1	1.66	2	3.32	2	3.32
	4	1	1.43	1	1.43	2	2.86
	5	0	0.00	2	2.57	2	2.57
Total		**23**	**47.63**	**20**	**41.36**	**27**	**54.39**

How about the book reviews data

- With the reviews data containing more than 2 million rows, it requires extremely large amount of memory to process.
- Therefore, I decided to base my recommendations on just the categories and description columns of the books data.

Limitations

1. I have not found a good solution for duplicate titles with spelling/wording differences.
2. I wish I was able to do this project with a cleaner dataset. For example, if I would be able to do this project with a dataset from a library catalog, it would usually have subject headings for the books which is a standardized list of subjects. The title and author columns would also be entered in a standardized format which would allow easy detection and handling of duplicates.
3. This dataset contains a very rich book ratings/reviews data which I haven't used much. Other NLP projects can be done using the ratings/reviews data.
4. I have not created a data input interface for users. This is out of the bounds of this project. But, if implemented, the system will need to consider spelling errors and variant titles.

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