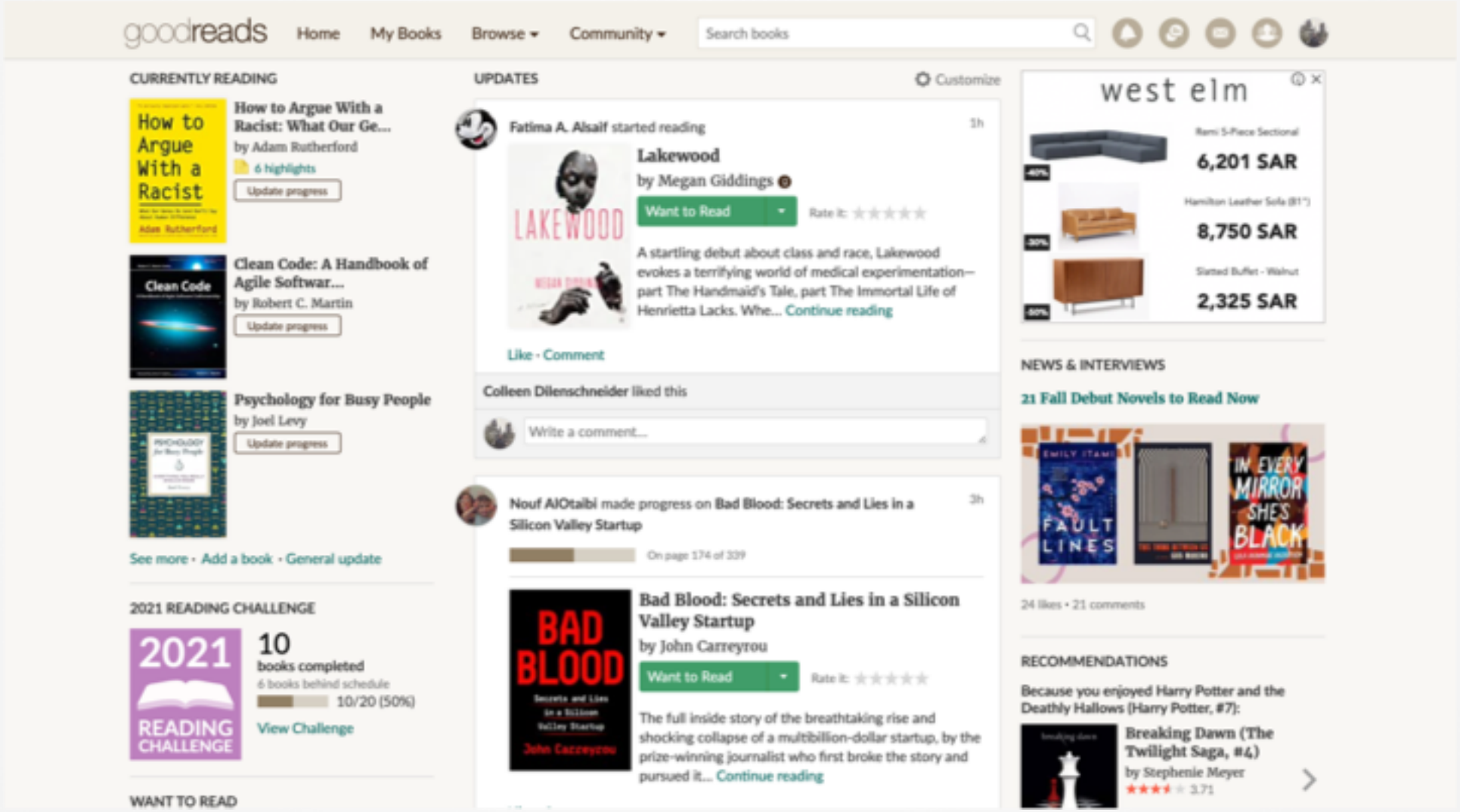
BOOK RECOMMENDATION SYSTEM

Yaqeen Al Mahdi

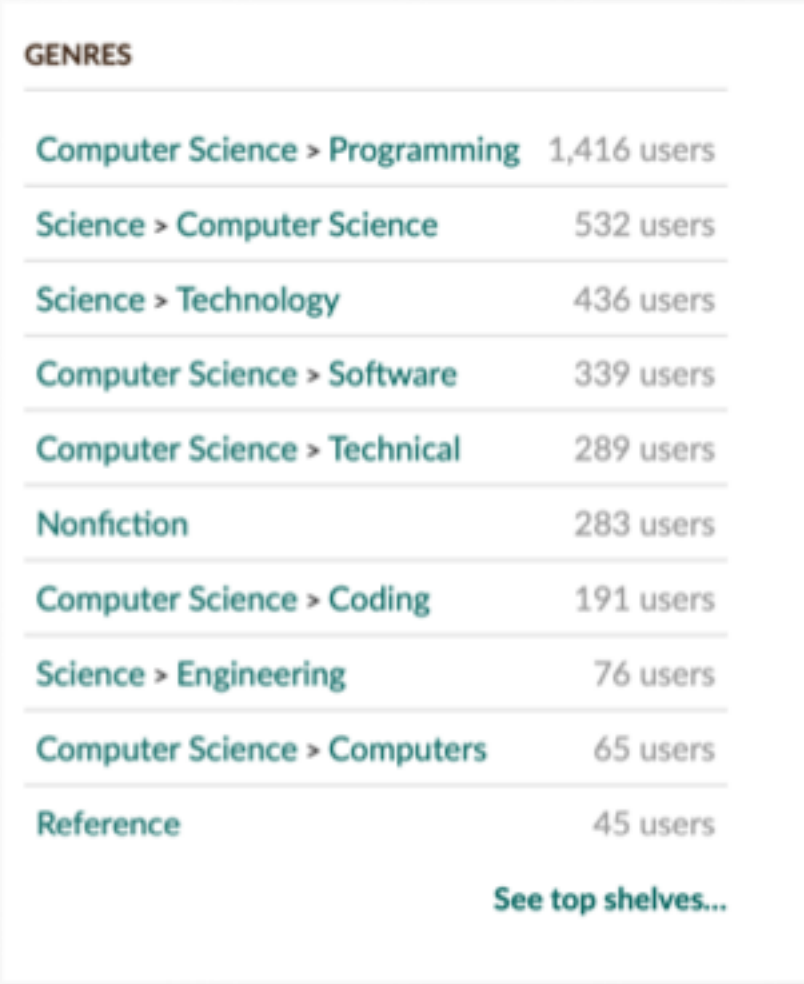
Outline

- Problem Description
- Data Preprocessing
- Data Acquisition
- Modeling Experiments
- Scope

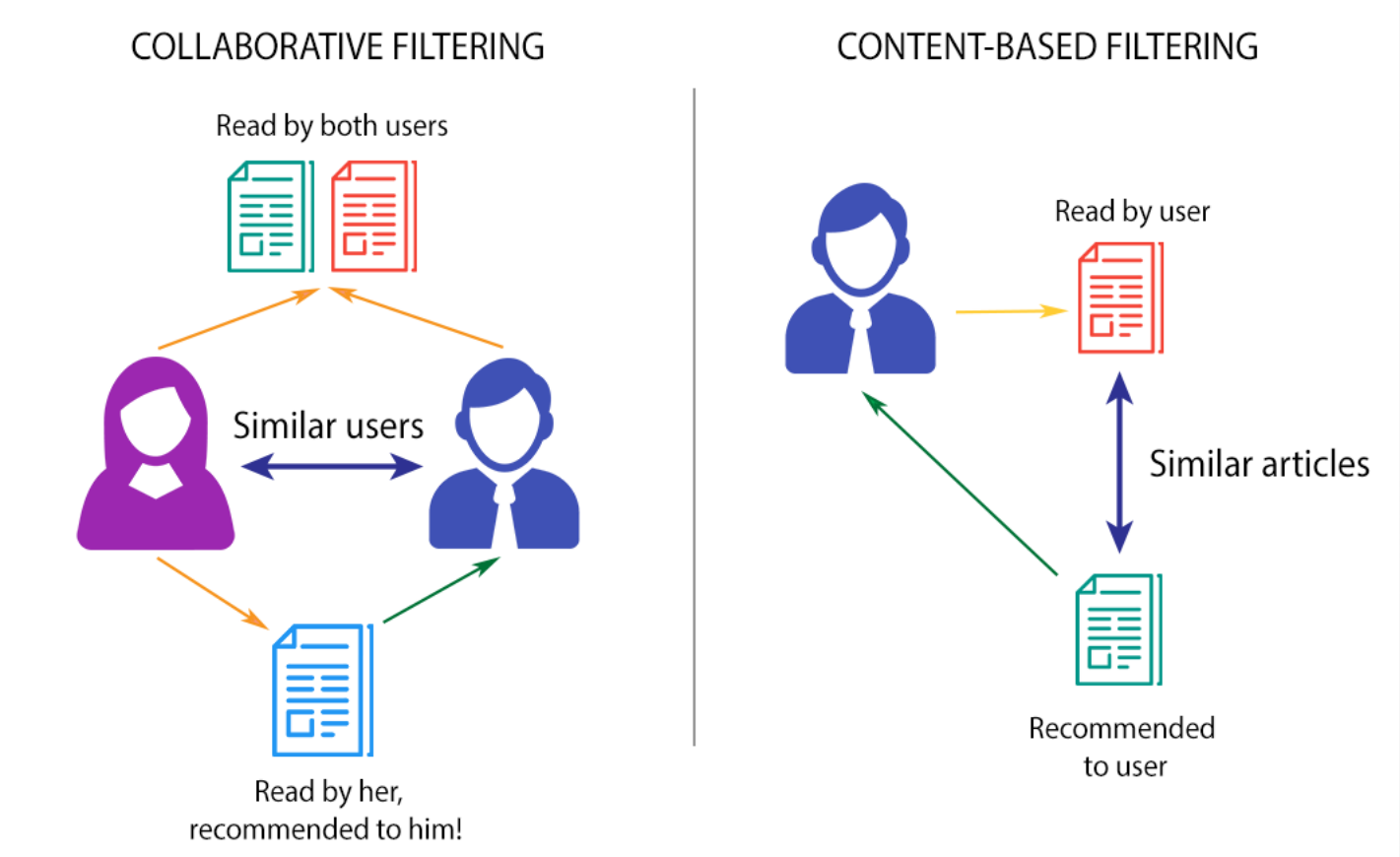
Problem Description



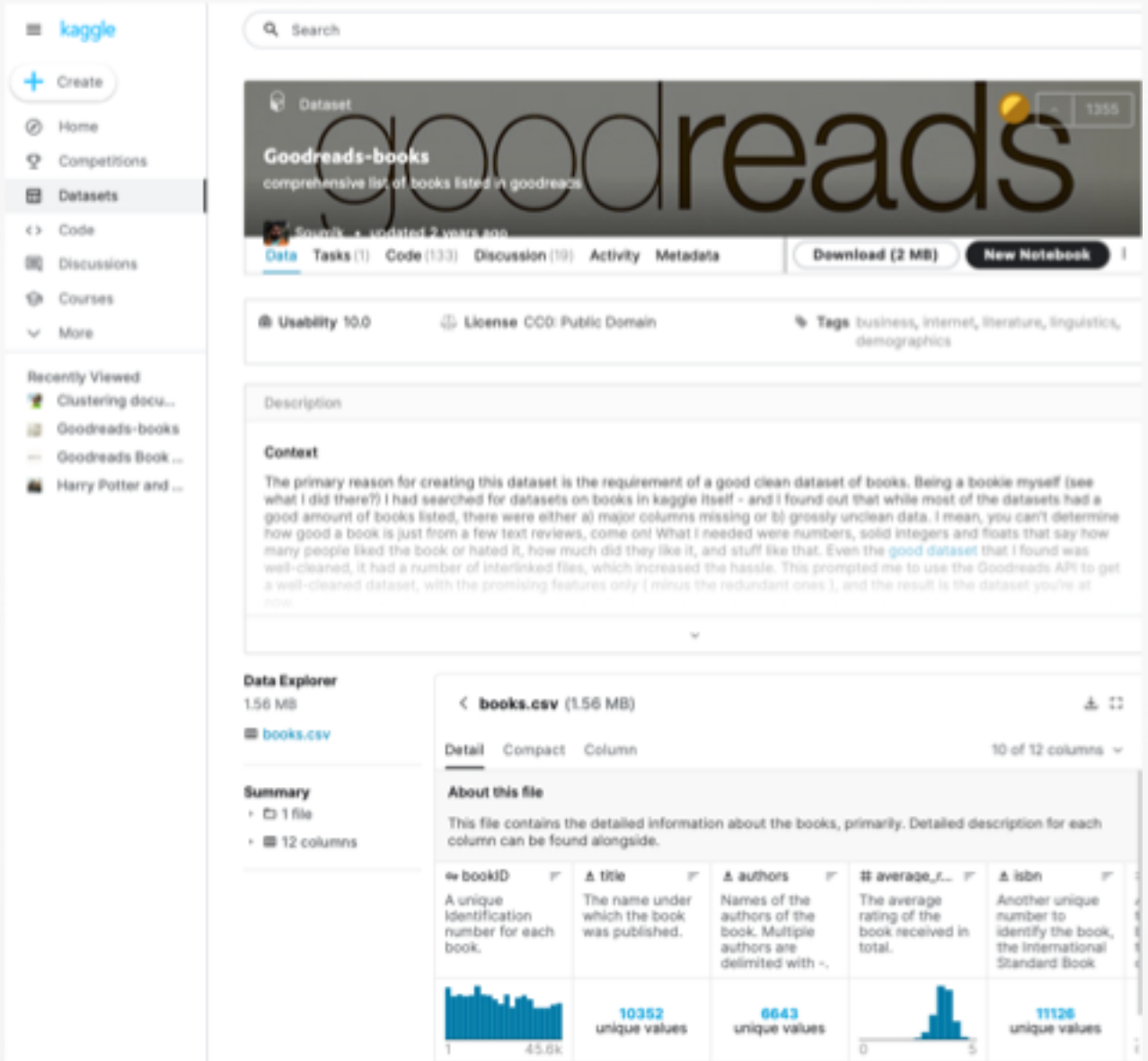
Problem Description



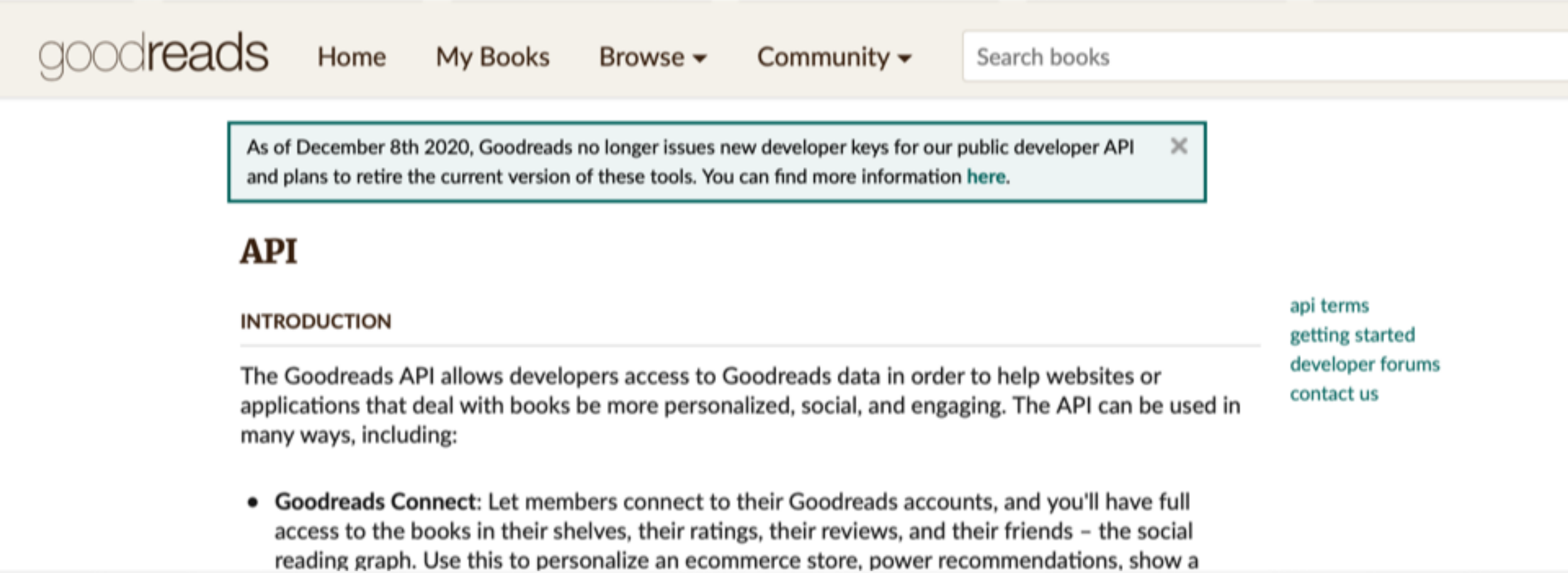
Problem Description



Data Acquisition



Data Acquisition



goodreads Home My Books Browse Community Search books

As of December 8th 2020, Goodreads no longer issues new developer keys for our public developer API and plans to retire the current version of these tools. You can find more information here.

API

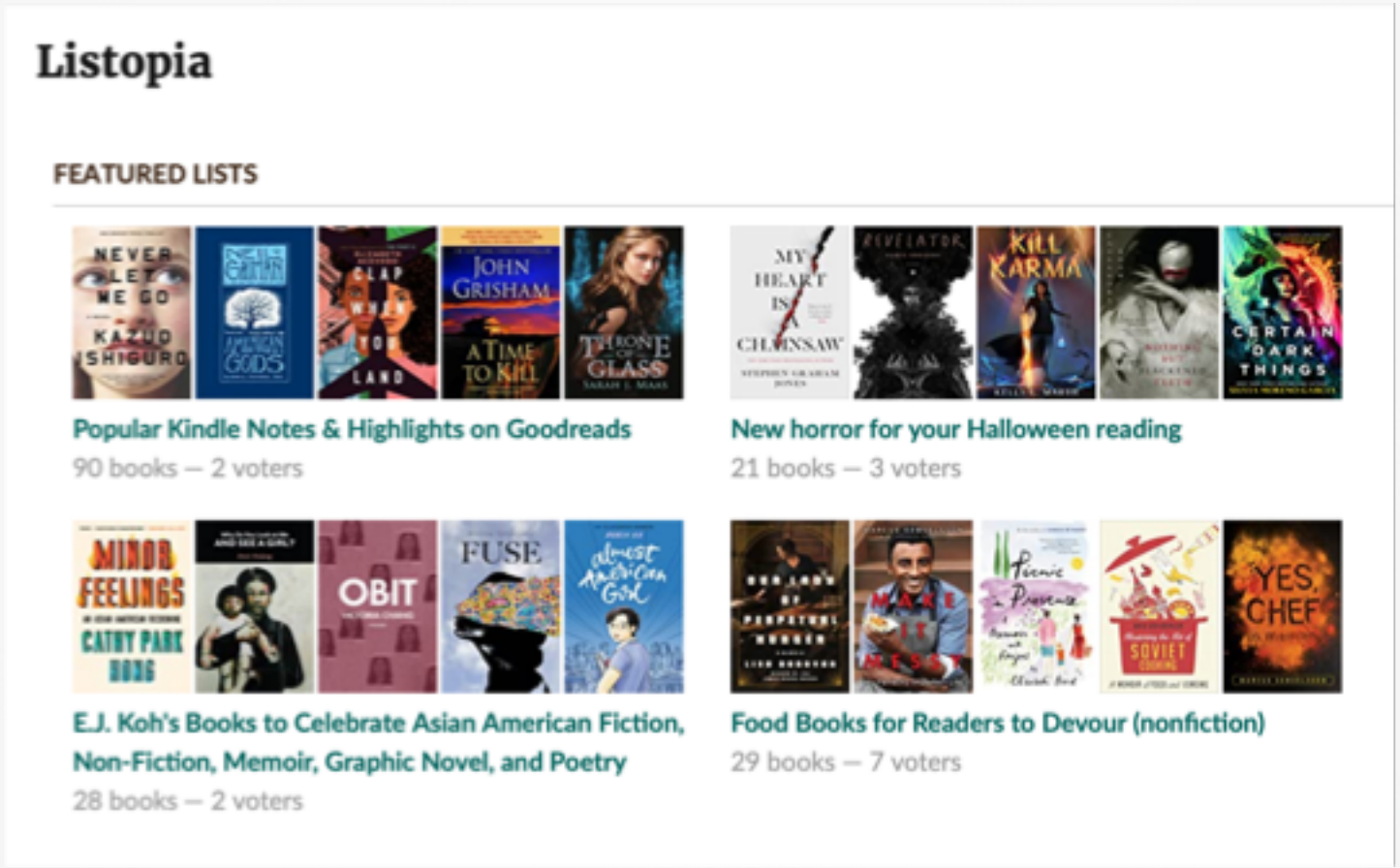
api terms
getting started
developer forums
contact us

INTRODUCTION

The Goodreads API allows developers access to Goodreads data in order to help websites or applications that deal with books be more personalized, social, and engaging. The API can be used in many ways, including:

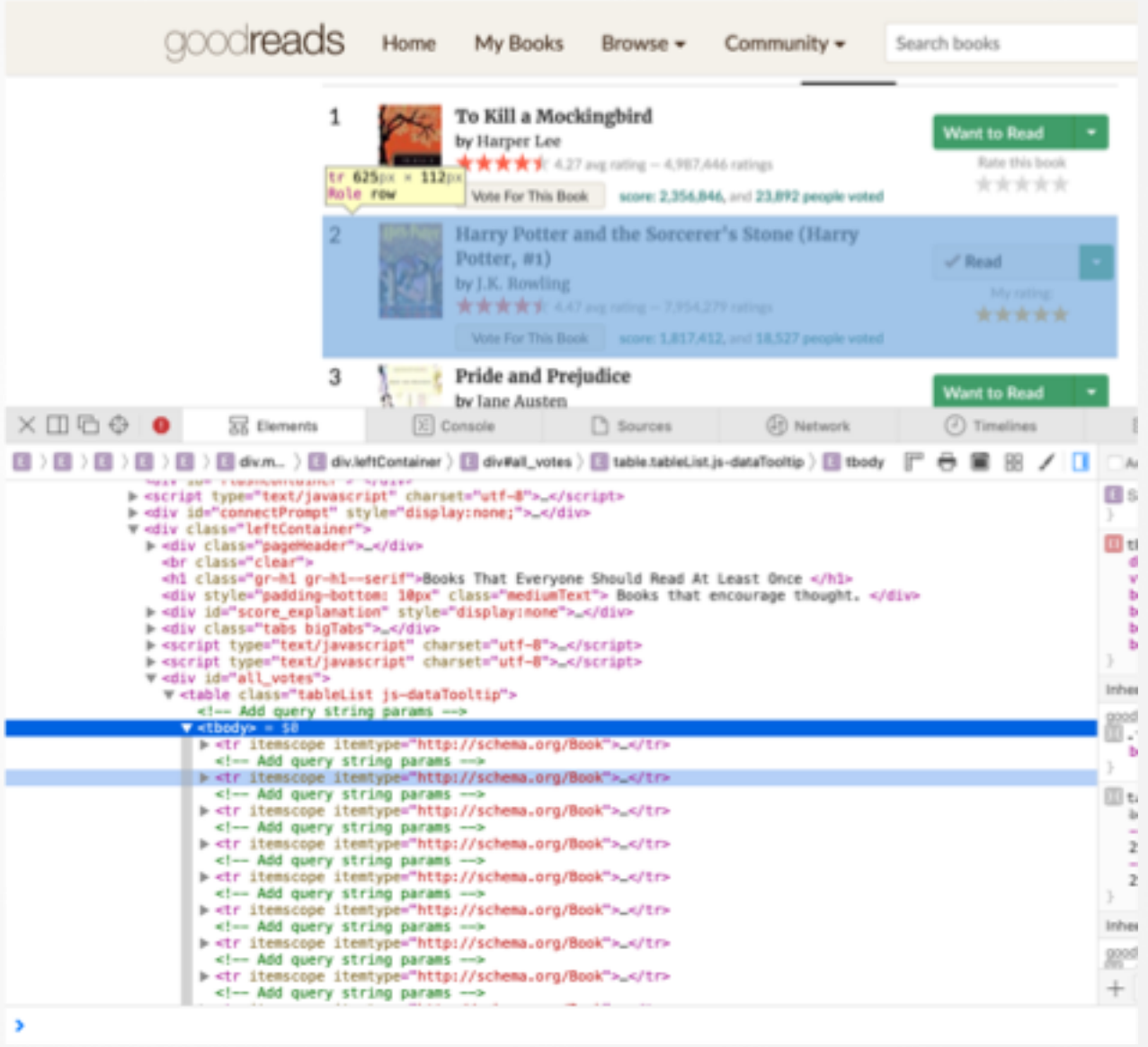
- **Goodreads Connect**: Let members connect to their Goodreads accounts, and you'll have full access to the books in their shelves, their ratings, their reviews, and their friends – the social reading graph. Use this to personalize an ecommerce store, power recommendations, show a

Data Acquisition



Data Acquisition

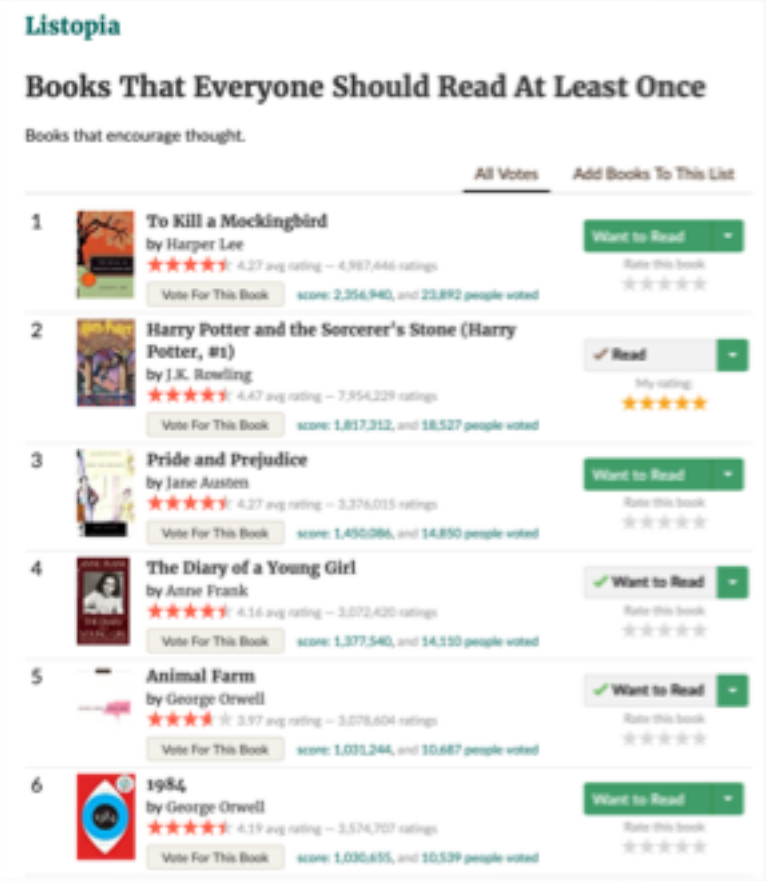
BeautifulSoap!



Data Acquisition


```python
def get_book_list(url):
    soup = BeautifulSoup(requests.get(url).text, "lxml")
    book_list = []
    pages_count = int(soup.find("div", class_="pagination").find_all("a")[-2].text)
    for p in range(1, page_count+1):
        soup = BeautifulSoup(requests.get("{}?page={}".format(url, p)).text, "lxml")
        book_list.extend([x["href"] for x in soup.find_all("a", class_="bookTitle", href=True)])

    return book_list
```



Data Acquisition


```
def get_book_list(url):
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    for p in range(1, page_count+1):
        soup = BeautifulSoup(requests.get("{}?page={}".format(url, p)).text, "lxml")
        book_list.extend([x["href"] for x in soup.find_all("a", class_="bookTitle", href=True)])

    return book_list
```

Data Acquisition


```
driver = webdriver.Safari()
dic = {"Title": [], "Author": [], "Description": [], "Publisher": [], "Year Published": [], "Genres": [], "Page Cou

for book in all_books[40000:50000]:
    driver.get("https://www.goodreads.com"+book)
    soup = BeautifulSoup(driver.page_source, "lxml")
    try:
        dic["Title"].append(soup.find("h1", id="bookTitle").text.strip())
    except:
        dic["Title"].append(None)

    try:
        dic["Author"].append([x.find("span", itemprop="name").text for x in soup.find_all("a", class_="authorName")
    except:
        dic["Author"].append(None)

    try:
        dic["Description"].append(soup.find("div", id="descriptionContainer").text.strip())
    except:
        dic["Description"].append(None)

    try:
        publishing_info = [x.strip() for x in soup.find("div", id="details").find_all(class_="row")[1].text.split("
    except:
        pass

    try:
        dic["Publisher"].append(find_publisher(publishing_info))
```

Scope

Collected Features:

- Title
- Author
- Description
- Publisher
- Year published
- Genres
- Page count

```
len(set([author for authors in df["Author"] for author in authors ]))
```

executed in 20ms, finished 19:37:09 2021-10-20

```
22425
```

```
genres = set()
for l in df["Genres"].values:
    genres = genres.union(set(l))

len(genres)
```

executed in 235ms, finished 10:38:35 2021-10-18

```
970
```

```
dict(genres.sum())
```

executed in 60ms, finished 18:05:22 2021-10-20

```
 'Poverty': 24,
 'Psychology': 1025,
 'Mental Illness': 226,
 'Vegan': 24,
 'Adventure': 2726,
 'Pre K': 4,
 'Music Biography': 8,
 'Wine': 3,
 'Ornithology': 4,
 'Eastern Africa': 44,
 'Royal Air Force': 1,
 'Helicopters': 1,
 'Cats': 42,
 'Beauty and The Beast': 23,
 'Political Science': 172,
 'Medievalism': 13,
 'Yuri': 2,
 'Chinese Literature': 16,
 'Liberia': 3,
 'Romanian Literature': 20,
```

Scope


```
def text_preprocessed(descriptions):

    description_processed = descriptions.apply(lambda x: x[376:-8])

    ### Remove anything that is not an alphabetical character, or a space.
    description_processed = description_processed.replace('[^a-zA-Z ]', " ", regex=True)

    ### Case unification
    description_processed = description_processed.apply(lambda x: x.lower())

    ### Stopword removal
    stopword_list = stopwords.words("english")
    description_processed = description_processed.apply(lambda x: [word for word in x.split() if word not in stc

    ### Bigrams
    phrase_model = Phrases(list(description_processed), min_count=1, threshold=1, connector_words=ENGLISH_CONNEC
    #df["Description_processed"] = [" ".join(phrase_model[sentence]) for sentence in df["Description_processed"]
    description_processed = [phrase_model[sentence] for sentence in description_processed]

    ### Stemming & Lemmatization
    description_processed = [" ".join([SnowballStemmer("english").stem(WordNetLemmatizer().lemmatize(word)) for

    return description_processed

df["Description_processed"] = text_preprocessed(df["Description"])
```

Experiment #1: TF-IDF and Cosine Similarity


```
tf = TfidfVectorizer(analyzer="word", ngram_range=(1,3), min_df=0, stop_words='english')
tfidf_matrix = tf.fit_transform(df["Description_processed"])
cos_sim = cosine_similarity(tfidf_matrix, tfidf_matrix)
cos_sim
```

```
def get_recommendations(book, cos_sim=cos_sim):
    idx = all_books[all_books == book].index[0] #index of the book at question
    scores = pd.Series(cos_sim[idx]).sort_values(ascending=False)
    #The highest is going to be the book itself, so we exclude it
    top_10_idx = scores.iloc[1:11].index
    return scores[1:11], all_books.loc[top_10_idx]
```

Experiment #1: TF-IDF and Cosine Similarity


```
scores, recommendations = get_recommendations('Harry Potter and the Deathly Hallows')
```

executed in 17ms, finished 10:52:15 2021-10-18

```
recommendations
```

executed in 4ms, finished 10:52:15 2021-10-18

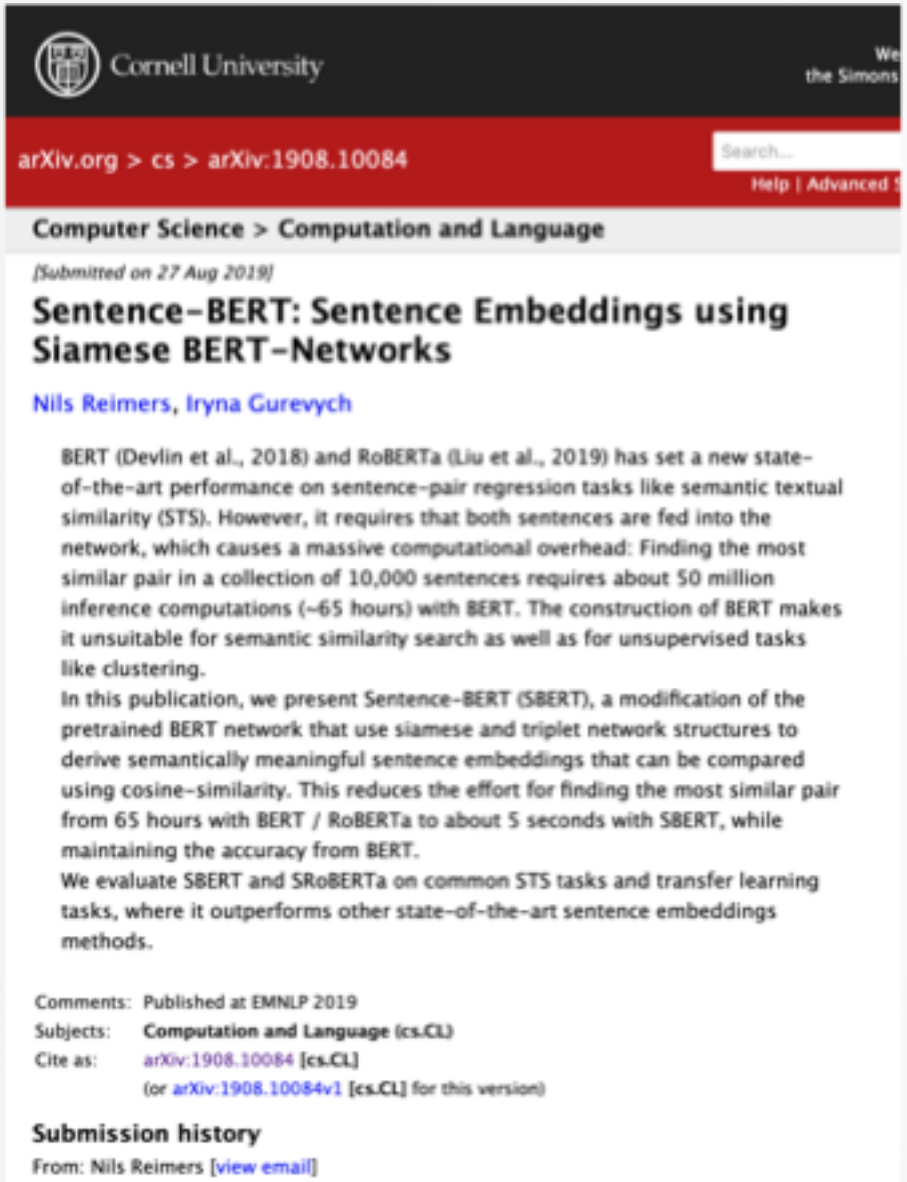
```
23806                                Stories Of The Prophets
20101                                        The Iron Lance
22243                                           Mr. Psychic
6703     The Man Who Ate His Boots: The Tragic History ...
6283                           The Loneliest Vampire in NYC
22139                                               Forever
24850                                            Futureland
22715                                    'Til the World Ends
19822    Zero to One: Notes on Startups, or How to Buil...
7055                                             Possessed
Name: Title, dtype: object
```

```
scores
```

executed in 4ms, finished 09:22:45 2021-10-18

```
23806    0.020658
20101    0.016718
22243    0.016594
6703     0.016182
6283     0.013223
22139    0.012986
24850    0.012597
22715    0.012443
19822    0.012252
7055     0.012045
dtype: float64
```

Experiment #2: Sentence Transformers/BERT and Cosine Similarity



Cornell University

arXiv.org > cs > arXiv:1908.10084

Computer Science > Computation and Language

[Submitted on 27 Aug 2019]

Sentence-BERT: Sentence Embeddings using Siamese BERT-Networks

Nils Reimers, Iryna Gurevych

BERT (Devlin et al., 2018) and RoBERTa (Liu et al., 2019) has set a new state-of-the-art performance on sentence-pair regression tasks like semantic textual similarity (STS). However, it requires that both sentences are fed into the network, which causes a massive computational overhead: Finding the most similar pair in a collection of 10,000 sentences requires about 50 million inference computations (~65 hours) with BERT. The construction of BERT makes it unsuitable for semantic similarity search as well as for unsupervised tasks like clustering.

In this publication, we present Sentence-BERT (SBERT), a modification of the pretrained BERT network that use siamese and triplet network structures to derive semantically meaningful sentence embeddings that can be compared using cosine-similarity. This reduces the effort for finding the most similar pair from 65 hours with BERT / RoBERTa to about 5 seconds with SBERT, while maintaining the accuracy from BERT.

We evaluate SBERT and SRoBERTa on common STS tasks and transfer learning tasks, where it outperforms other state-of-the-art sentence embeddings methods.

Comments: Published at EMNLP 2019
Subjects: Computation and Language (cs.CL)
Cite as: arXiv:1908.10084 [cs.CL]
(or arXiv:1908.10084v1 [cs.CL] for this version)

Submission history

From: Nils Reimers [view email]

Bidirectional Encoder Representations: a transformer-based machine learning technique for natural language processing pre-training developed by Google.

Experiment #2: Sentence Transformers/BERT and Cosine Similarity


```
model = SentenceTransformer('paraphrase-MiniLM-L6-v2')

#Our sentences we like to encode
sentences = list(df["Description_processed"])

#Sentences are encoded by calling model.encode()
embeddings = model.encode(sentences)
```

executed in 13m 37s, finished 13:07:30 2021-10-18

```
books_embeddings = list(zip(df["Title"], df["Description"], embeddings))
```

executed in 169ms, finished 13:07:31 2021-10-18

```
cos_sim_embeddings = cosine_similarity(embeddings,embeddings)
```

executed in 10.6s, finished 13:07:41 2021-10-18

```
scores, recommendations = get_recommendations('Harry Potter and the Deathly Hallows', cos_sim_embeddings)
```

executed in 12ms, finished 13:07:59 2021-10-18

```
scores
```

executed in 6ms, finished 13:08:00 2021-10-18

```
19670    0.788545
16027    0.770192
1896     0.763471
20293    0.763228
11736    0.763059
9089     0.762973
2401     0.760832
9913     0.758609
12702    0.758377
21936    0.755704
dtype: float32
```

Experiment #2: Sentence Transformers/BERT and Cosine Similarity


```
recommendations
```

executed in 6ms, finished 13:08:03 2021-10-18

```
19670                                                Waterbound
16027                                     Keturah and Lord Death
1896      The Ignorant Maestro: How Great Leaders Inspir...
20293                                          Emily of New Moon
11736                                                Headlong
9089                                      The End of the Matter
2401                                          Kidnapped Hearts
9913      The Most Interesting Person in the Room: A bri...
12702                          The Greeks and the Irrational
21936                                                Corbenic
Name: Title, dtype: object
```

Experiment #2: Sentence Transformers/BERT and Cosine Similarity

CMU Book Summary Dataset

The CMU Book Summary Dataset supports ongoing work described in:

David Bamman and Noah Smith (2013), "New Alignment Methods for Discriminative Book Summarization," [ArXiv]

booksummaries.tar.gz [17M]

This dataset contains plot summaries for 16,559 books extracted from Wikipedia, along with aligned metadata from Freebase, including book author, title, and genre.

All data is released under a Creative Commons Attribution-ShareAlike License. For questions or comments, please contact David Bamman (dbamman@cs.cmu.edu).

Example

The following example illustrates the data and metadata available for Don DeLillo's *White Noise*.

Book metadata

Wikipedia ID	1166383
Freebase ID	/m/04cvx9
Book title	White Noise
Book author	Don DeLillo
Publication date	1985-01-21
Genres	Novel, Postmodernism, Speculative fiction, Fiction

Plot summary

Set at a bucolic Midwestern college known only as The-College-on-the-Hill, White Noise follows a year in the life of Jack Gladney, a professor who has made his name by pioneering the field of Hitler Studies (though he hasn't taken German language lessons until this year). He has been married five times to four women and has a brood of children and stepchildren (Heinrich, Denise, Steffie, Wilder) with his current wife, Babette. Jack and Babette are both extremely afraid of death;

```
df2.shape
```

executed in 5ms, finished 13:41:17 2021-10-18

```
(16559, 8)
```

```
df2["Summary_processed"] = text_preprocessed(df2["Plot Summary"])
```

executed in 1m 17.7s, finished 13:31:48 2021-10-18

```
model = SentenceTransformer('paraphrase-MiniLM-L6-v2')

#Our sentences we like to encode
sentences = list(df2["Summary_processed"])

#Sentences are encoded by calling model.encode()
embeddings = model.encode(sentences)
```

executed in 8m 29s, finished 13:41:04 2021-10-18

```
books_embeddings = list(zip(df2["Book title"], embeddings))
```

executed in 47ms, finished 13:41:26 2021-10-18

```
cos_sim_embeddings = cosine_similarity(embeddings,embeddings)
```

executed in 3.45s, finished 13:41:33 2021-10-18

```
scores, recommendations = get_recommendations("Harry Potter and the Philosopher's Stone", cos_sim_embeddings)
```

executed in 12ms, finished 13:42:47 2021-10-18

```
scores
```

executed in 5ms, finished 13:42:58 2021-10-18

```
480      0.799137
948      0.755065
12207    0.750974
15186    0.749860
445      0.747034
716      0.737015
724      0.734902
7677     0.731284
13090    0.717387
4841     0.716605
dtype: float32
```

```
recommendations
```

executed in 4ms, finished 13:43:01 2021-10-18

```
480        Harry Potter and the Chamber of Secrets
948                                  Tik-Tok of Oz
12207                          House of Many Ways
15186                  Necroscope V: Deadspawn
445      Harry Potter and the Order of the Phoenix
716       Harry Potter and the Prisoner of Azkaban
724            Harry Potter and the Goblet of Fire
7677                                 Hidden Warrior
13090                  The Great Ghost Rescue
4841                        The Witching Hour
Name: Book title, dtype: object
```

Experiment #3: Embedding with Clustering


```
clustering_model = DBSCAN(eps=3, min_samples=2).fit(embeddings)
cluster_assignment = clustering_model.labels_
```

```
pd.DataFrame(np.unique(cluster_assignment, return_counts=True)).T
```

Experiment #3: Embedding with Clustering


```
pd.DataFrame(np.unique(cluster_assignment, return_counts=True)).T
```

executed in 19ms, finished 14:54:23 2021-10-18

	0	1
0	-1	14110
1	0	252
2	1	1715
3	2	2
4	3	2
...	...	...
186	185	3
187	186	2
188	187	2
189	188	2
190	189	2

191 rows × 2 columns

Thank You