Intro to content-based recommendations

BUILDING RECOMMENDATION ENGINES IN PYTHON

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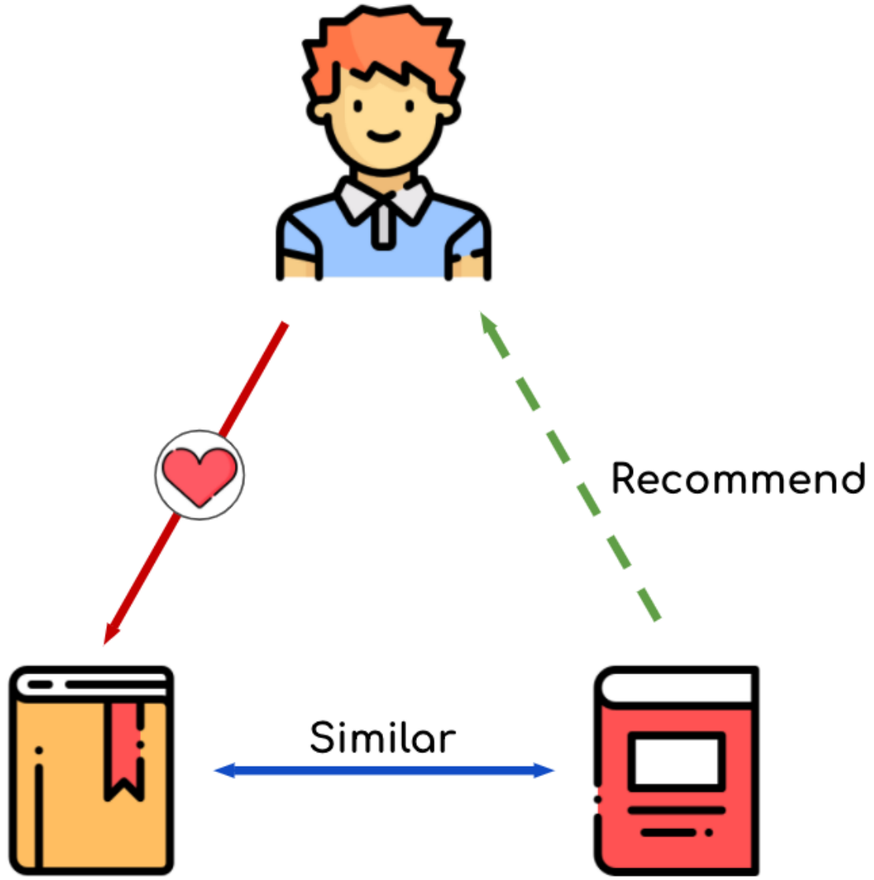
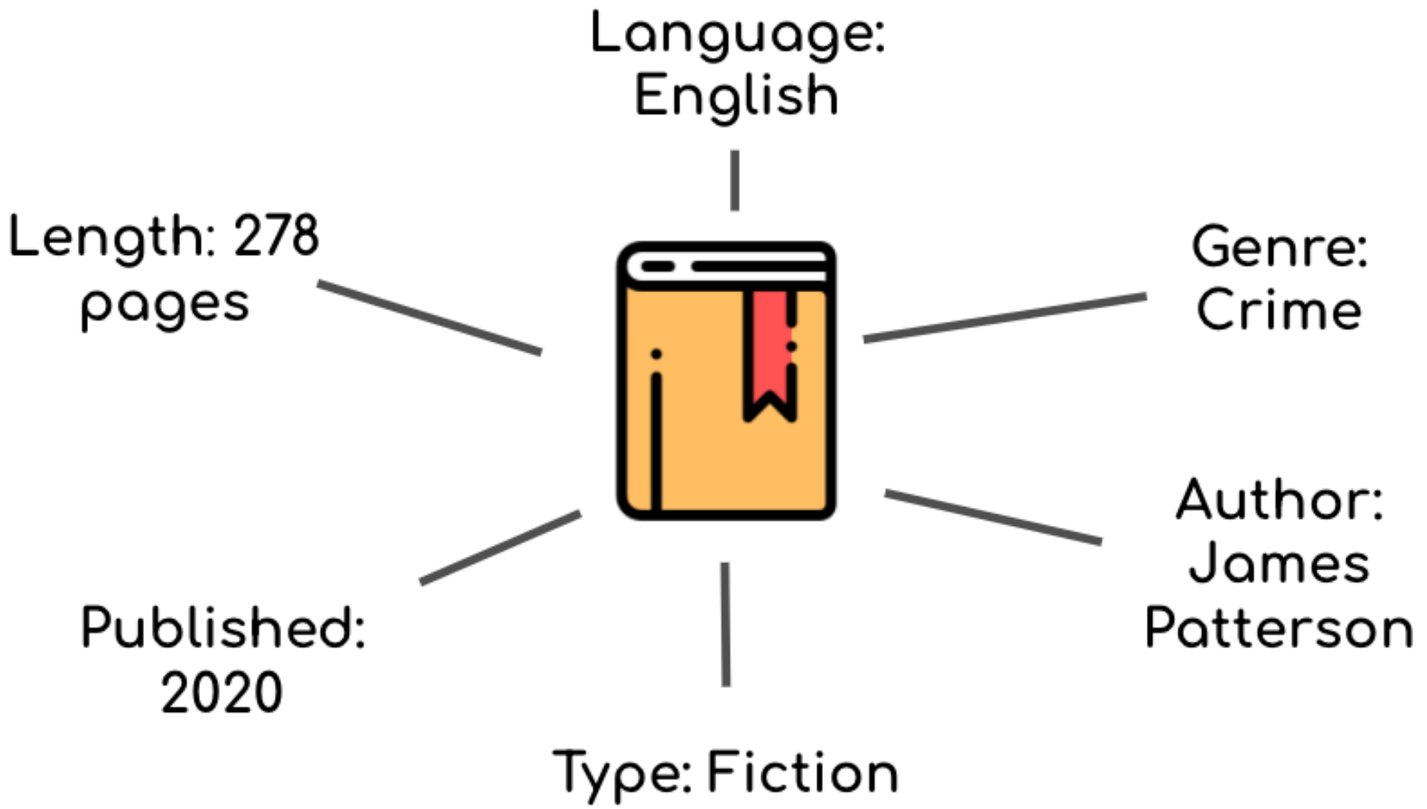
What are content-based recommendations?



Items' attributes or characteristics



Vectorizing your attributes

ITEM	Attribute 1	Attribute 2	Attribute 3	Attribute 4
Item_001	0	1	1	0
Item_002	1	0	1	0
Item_003	0	1	0	1

One to many relationships

Book	Genre
The Hobbit	Adventure
The Hobbit	Fantasy
The Great Gatsby	Tragedy
...	...

Book	Adventure	Fantasy	Tragedy	...
The Hobbit	1	1	0	...
The Great Gatsby	0	0	1	...
...	...	...	...	...

Crosstabulation

```
pd.crosstab(                              ,                              )
```

Crosstabulation

```
pd.crosstab(book_genre_df['Book'], book_genre_df['Genre'])
```

Book	Adventure	Fantasy	Tragedy	Social commentary
The Hobbit	1	1	0	0
The Great Gatsby	0	0	1	1
A Game of Thrones	0	1	0	0
Macbeth	0	0	1	0
...	...	...	...	...

Let's practice!

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Making content-based recommendations

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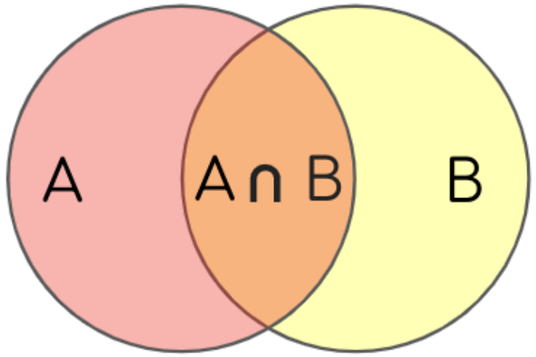
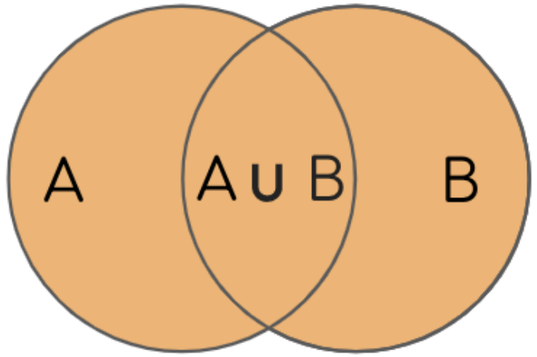
Introducing the Jaccard similarity

Jaccard similarity:



The number of attributes that two items have in common



The total number of their combined attributes

$$J(A,B) = \frac{A \cap B}{A \cup B}$$

Calculating Jaccard similarity between books

`genres_array_df` :

Book	Adventure	Fantasy	Tragedy	Social commentary	...
The Hobbit	1	1	0	0	...
The Great Gatsby	0	0	1	1	...
A Game of Thrones	0	1	0	0	...
Macbeth	0	0	1	0	...
...	...	...	...	...	...

Calculating Jaccard similarity between books

```
from sklearn.metrics import jaccard_score


hobbit_row = book_genre_df.loc['The Hobbit']
GOT_row = book_genre_df.loc['A Game of Thrones']


print(jaccard_score(hobbit_row, GOT_row))
```

```
0.5
```

Finding the distance between all items

```
from scipy.spatial.distance import pdist, squareform

jaccard_distances = pdist(book_genre_df.values, metric='jaccard')
print(jaccard_distances)
```

```
[1.  0.5 1.  1.  0.5 1. ]
```

```
square_jaccard_distances = squareform(jaccard_distances)
print(square_jaccard_distances)
```

```
[[0.  1.  0.5 1. ]
 [1.  0.  1.  0.5]
 [0.5 1.  0.  1. ]
 [1.  0.5 1.  0. ]]
```

Finding the distance between all items

```
print(square_jaccard_distances)
```

```
[[0.  1.  0.5 1. ]
 [1.  0.  1.  0.5]
 [0.5 1.  0.  1. ]
 [1.  0.5 1.  0. ]]
```

```
jaccard_similarity_array = 1 -  square_jaccard_distances
print(jaccard_similarity_array)
```

```
[[1.  0.  0.5 0. ]
 [0.  1.  0.  0.5]
 [0.5 0.  1.  0. ]
 [0.  0.5 0.  1. ]]
```

Creating a usable distance table

```
distance_df = pd.DataFrame(jaccard_similarity_array,
                           index=genres_array_df['Book'],
                           columns=genres_array_df['Book'])
distance_df.head()
```

```
                The Hobbit  The Great Gatsby  A Game of Thrones  Macbeth  ...
The Hobbit            1.00              0.15               0.75     0.01  ...
The Great Gatsby      0.15              1.00               0.01     0.43  ...
...
```

Comparing books

```
print(distance_df['The Hobbit']['A Game of Thrones'])
```

```
0.75
```

```
print(distance_df['The Hobbit']['The Great Gatsby'])
```

```
0.15
```

Finding the most similar books

```
print(distance_df['The Hobbit'].sort_values(ascending=False))
```

```
title
The Hobbit                                                    1.00
The Two Towers                                                0.91
A Game of Thrones                                             0.50
...
```

Let's practice!

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Text-based similarities

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Working without clear attributes

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Item Description

Term frequency inverse document frequency

$$\text{TF-IDF} = \frac{\frac{\text{Count of word occurrences}}{\text{Total words in document}}}{\log(\frac{\text{Number of docs word is in}}{\text{Total number of docs}})}$$

Our data

`book_summary_df` :

Book	Description
The Hobbit	"Bilbo Baggins lives a simple life with his fellow hobbits in the shire..."
The Great Gatsby	"Set in Jazz Age New York, the novel tells the tragic story of Jay ..."
A Game of Thrones	"15 years have passed since Robert's rebellion, with a nine-year-long ..."
Macbeth	"A brave Scottish general receives a prophecy from a trio of witches ..."
...	...

Instantiate the vectorizer

```
from sklearn.feature_extraction.text import TfidfVectorizer
```

```
tfidfvec = TfidfVectorizer(         ,             )
```

Filtering the data

```
from sklearn.feature_extraction.text import TfidfVectorizer
```

```
tfidfvec = TfidfVectorizer(min_df=2,           )
```

Filtering the data

```
from sklearn.feature_extraction.text import TfidfVectorizer
```

```
tfidfvec = TfidfVectorizer(min_df=2, max_df=0.7)
```

Vectorizing the data

```
vectorized_data = tfidfvec.fit_transform(book_summary_df['Descriptions'])
print(tfidfvec.get_feature_names)
```

```
['age', 'ancient', 'angry', 'brave', 'battle', 'fellow', 'game', 'general', ...]
```

```
print(vectorized_data.to_array())
```

```
[[0.21,      0.53,    0.41,    0.64,     0.01,     0.02,      ...
 [0.31,      0.00,    0.42,    0.03,     0.00,     0.73,      ...
 [...,         ...,     ...,     ...,      ...,      ...,      ...
```

Formatting the data

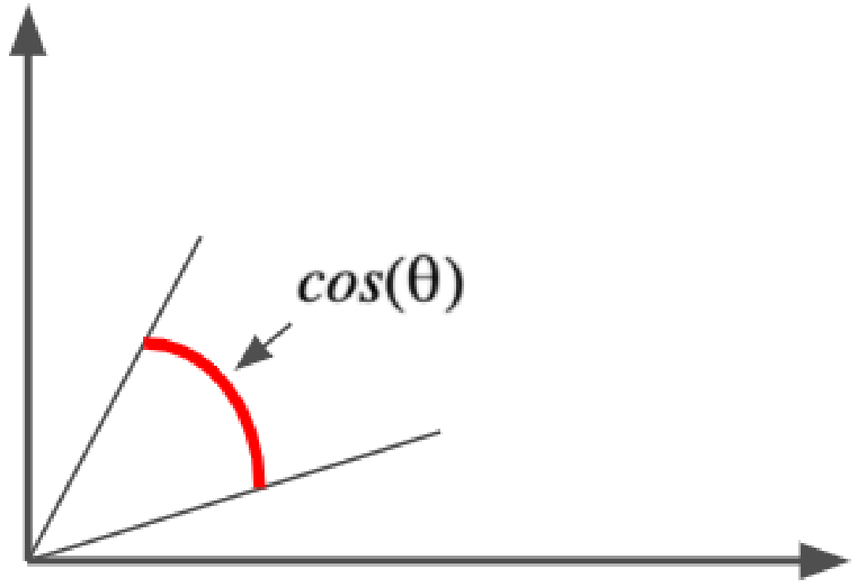
```
tfidf_df = pd.DataFrame(vectorized_data.toarray(),
                        columns=tfidfvec.get_feature_names())
tfidf_df.index = book_summary_df['Book']
print(tfidf_df)
```

```
                  | 'age'| 'ancient'| 'angry'| 'brave'| 'battle'| 'fellow'|...
|-----------------|------|----------|--------|--------|---------|---------|...
| The Hobbit      |  0.21|      0.53|    0.41|    0.64|     0.01|     0.02|...
| The Great Gatsby |  0.31|      0.00|    0.42|    0.03|     0.00|     0.73|...
| A Game of Thrones|  0.61|      0.42|    0.77|    0.31|     0.83|     0.03|...
|              ...|   ...|       ...|     ...|     ...|      ...|      ...|...
```

Cosine similarity

Cosine Distance:

$$cos(\theta) = \frac{A.B}{||A|| \cdot ||B||}$$



Cosine similarity

```
from sklearn.metrics.pairwise import cosine_similarity


# Find similarity between all items
cosine_similarity_array = cosine_similarity(tfidf_summary_df)
```

```
# Find similarity between two items
cosine_similarity(tfidf_df.loc['The Hobbit'].values.reshape(1, -1),
                  tfidf_df.loc['Macbeth'].values.reshape(1, -1))
```

Let's practice!

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User profile recommendations

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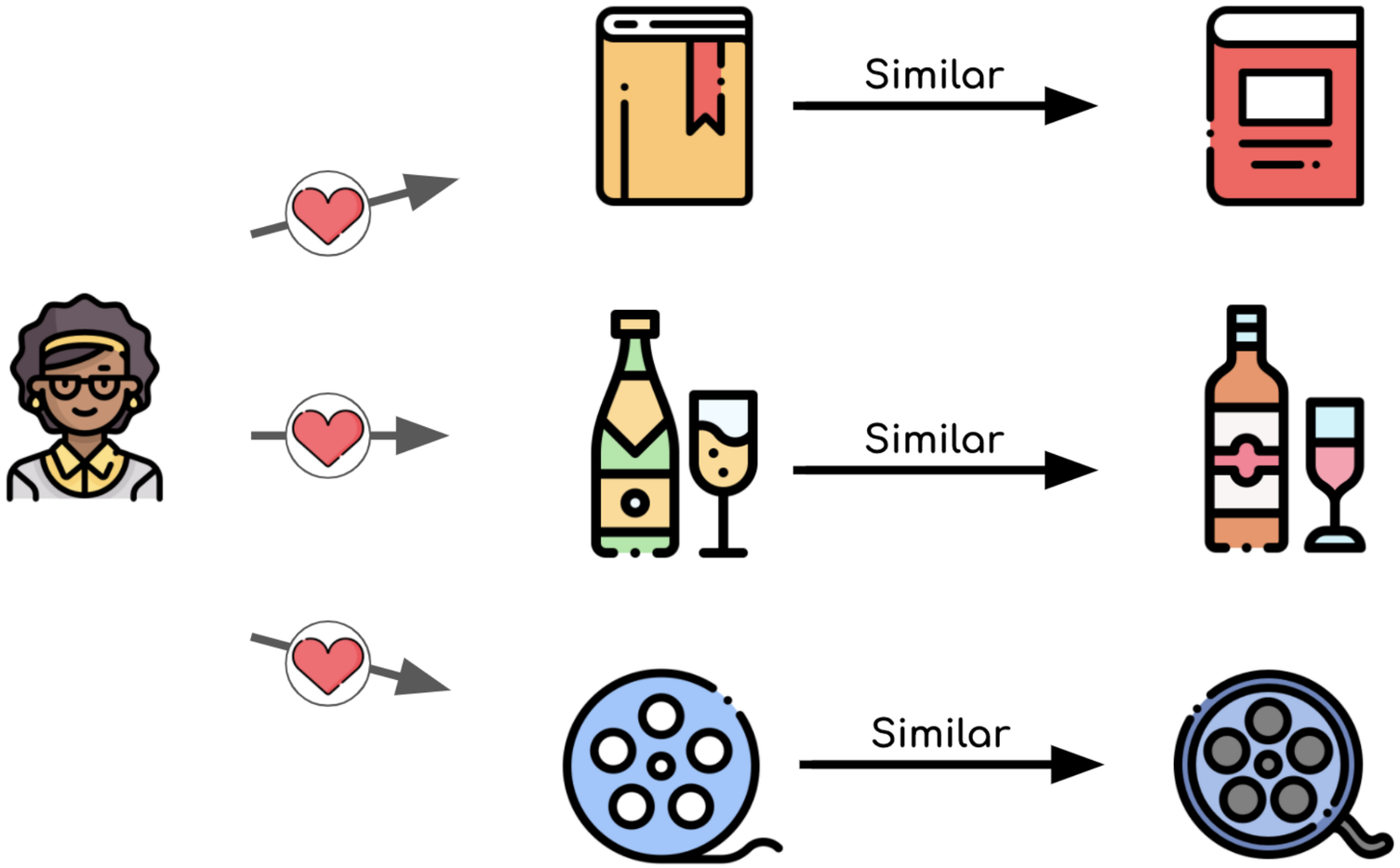
Item to item recommendations



User profiles

`tfidf_summary_df` :

Book	Adventure	Fantasy	Tragedy	Social commentary
The Hobbit	1	1	0	0
Macbeth	0	0	1	0
...	...	...	...	...

User Profile:

User Profile	Adventure	Fantasy	Tragedy	Social commentary
User_001	???	???	???	???

Extract the user data

```
list_of_books_read = ['The Hobbit', 'Foundation', 'Nudge']
user_books = tfidf_summary_df.reindex(list_of_books_read)
print(user_books)
```

```
              age   ancient   angry   brave   battle   fellow    ...
The Hobbit   0.21      0.53    0.41    0.64     0.01     0.02    ...
Foundation   0.31      0.90    0.42    0.33     0.64     0.04    ...
     Nudge   0.61      0.01    0.45    0.31     0.12     0.74    ...
```

Build the user profile

```
user_prof = user_movies.mean()
print(user_prof)
```

```
age       0.376667
ancient   0.480000
angry     0.426667
brave     0.256667
              ...
```

```
print(user_prof.values.reshape(1,-1))
```

```
[0.376667, .480000, 0.426667, 0.256667, ...]
```

Finding recommendations for a user

```
# Create a subset of only the non read books
non_user_movies = tfidf_summary_df.drop(list_of_movies_seen, axis=0)

# Calculate the cosine similarity between all rows
user_prof_similarities = cosine_similarity(user_prof.values.reshape(1, -1),
                                           non_user_movies)
# Wrap in a DataFrame for ease of use
user_prof_similarities_df = pd.DataFrame(user_prof_similarities.T,
                                         index=tfidf_summary_df.index,
                                         columns=["similarity_score"])
```

Getting the top recommendations

```
sorted_similarity_df = user_prof_similarities.sort_values(by="similarity_score",
                                                          ascending=False)
print(sorted_similarity_df)
```

```
                          similarity_score
Title
The Two Towers                    0.422488
Dune                              0.363540
The Magicians Nephew              0.316075
...                               ...
```

Let's practice!

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