

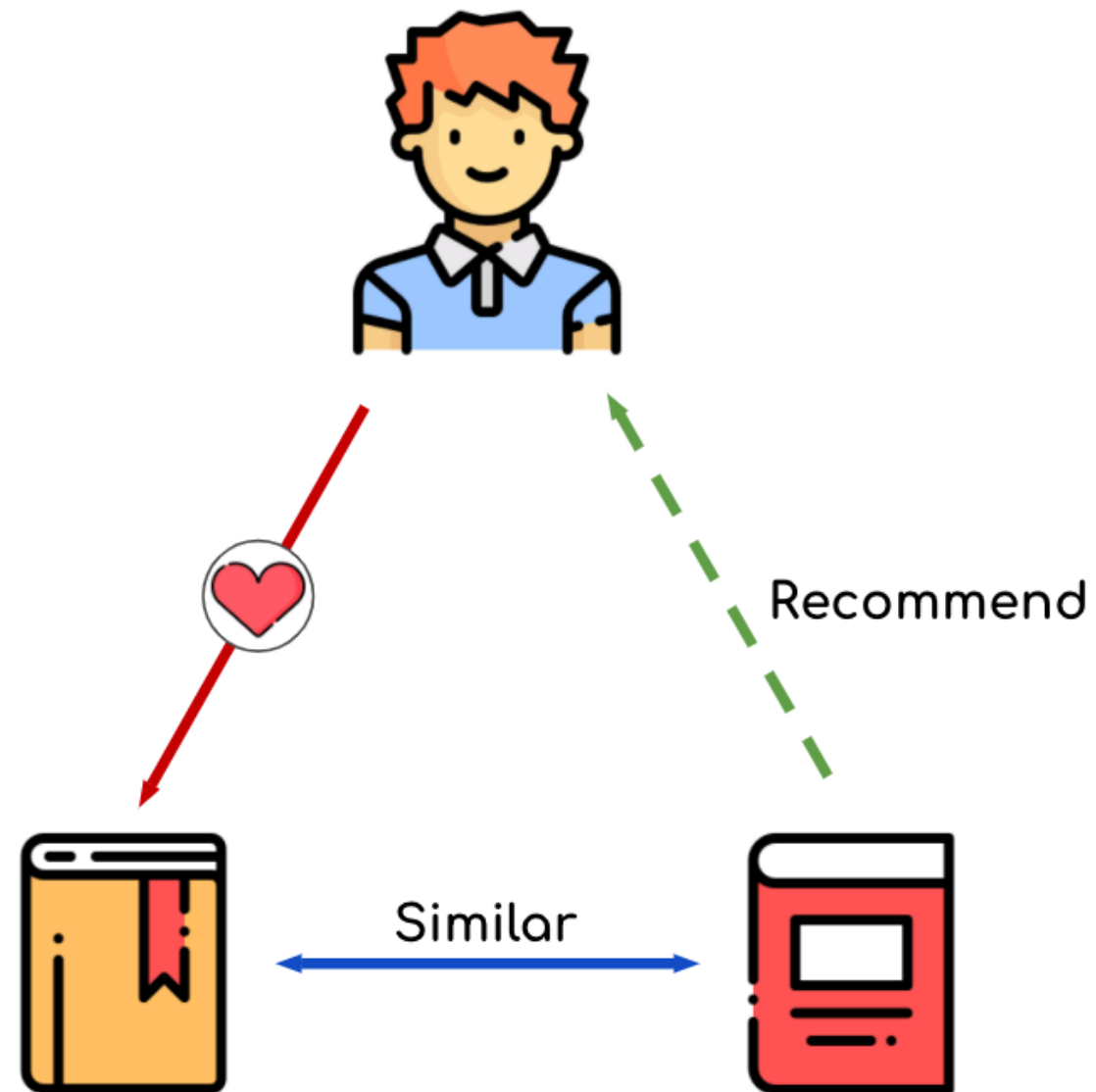
Intro to content-based recommendations

BUILDING RECOMMENDATION ENGINES IN PYTHON

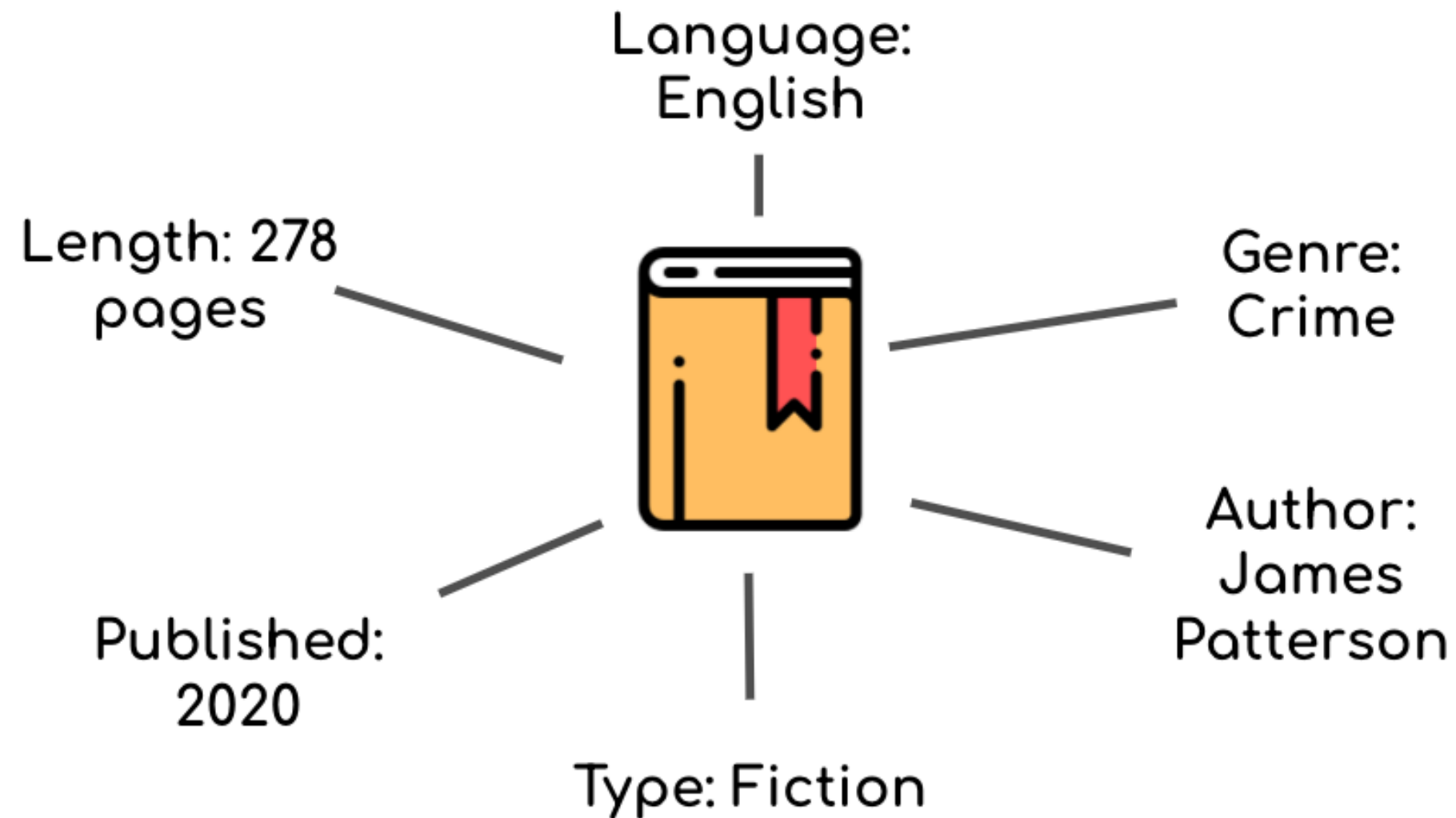


Rob O'Callaghan
Director of Data

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'])
```

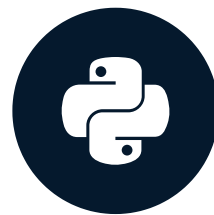
Book	Adventure	Fantasy	Tragedy	Social commentary
The Hobbit	1	1	0	0
The Great Gatsby	0	0	1	1
A Game of Thrones	0	1	0	0
Macbeth	0	0	1	0
...

Let's practice!

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Making content- based recommendations

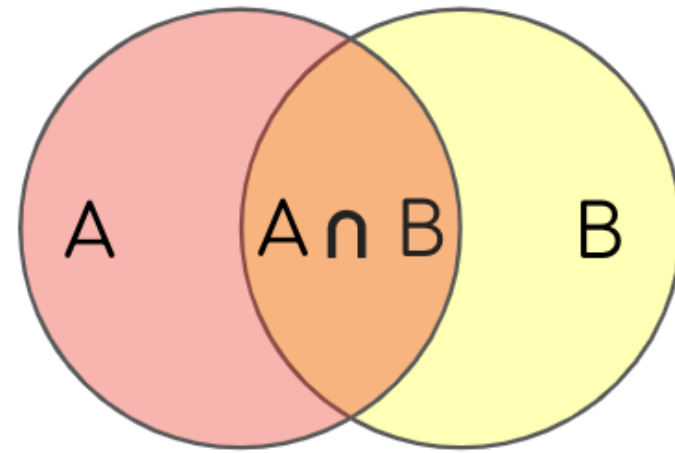
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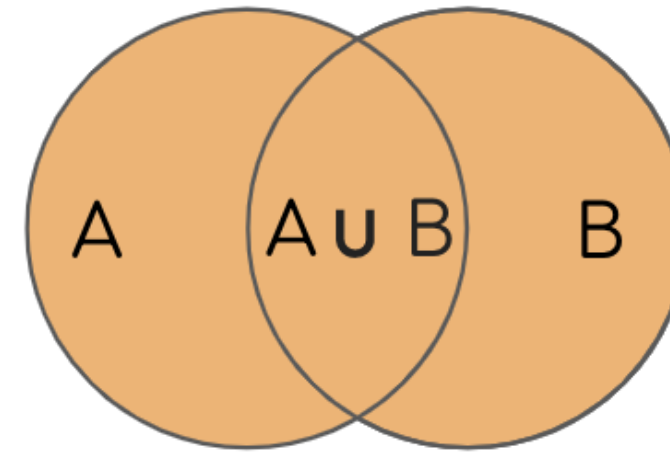
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Introducing the Jaccard similarity

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))
```

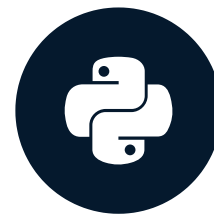
```
title
The Hobbit      1.00
The Two Towers  0.91
A Game of Thrones 0.50
...
```

Let's practice!

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Text-based similarities

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Director of Data

Working without clear attributes



Roll over image to zoom in

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- Easy open, recyclable package ships in simple recyclable packaging that's easy to open and frustration free, and the Play Doh cans and lids are also recyclable to help build a more sustainable world
- Notice to parents: contains wheat
- Just the right colors to start shape, squish, mix, and make it all. Great for lots of uses like Play Doh refills, as a Play Doh starter set, or as an add on to any Play Doh toy (sold separately)

[New & Used \(10\) from \\$7.35](#) & **FREE** Shipping on orders over \$25.00

Item
Description

Term frequency inverse document frequency

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

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())

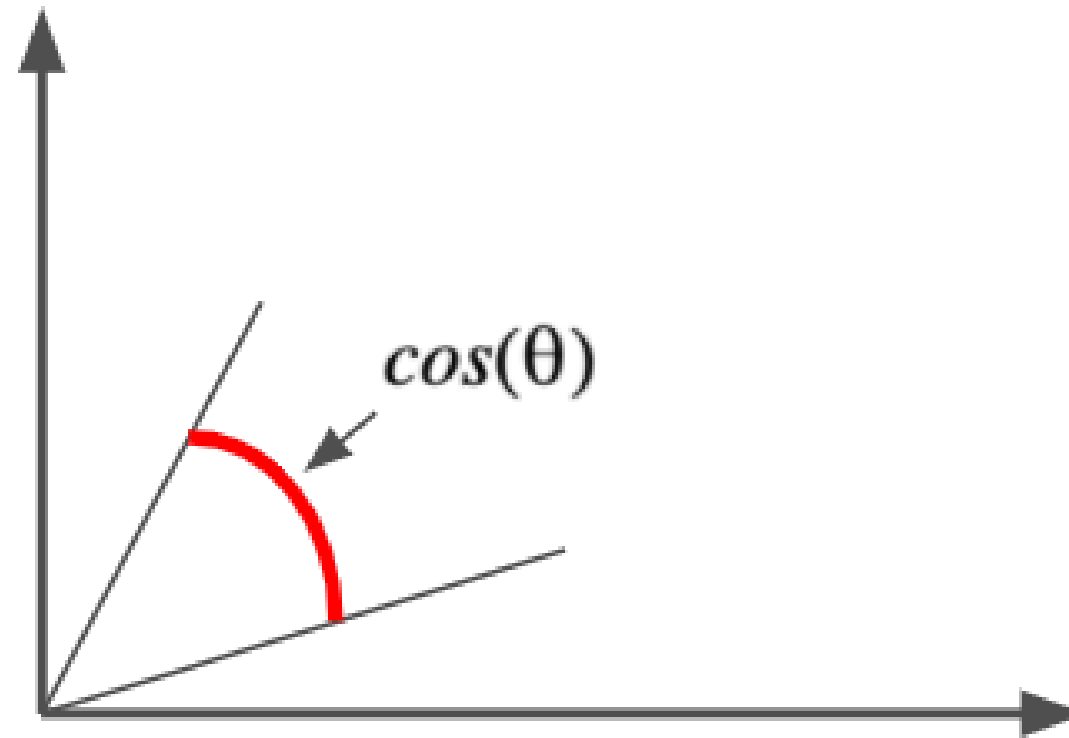
tfidf_df.index = book_summary_df['Book']
print(tfidf_df)
```

	'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:

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



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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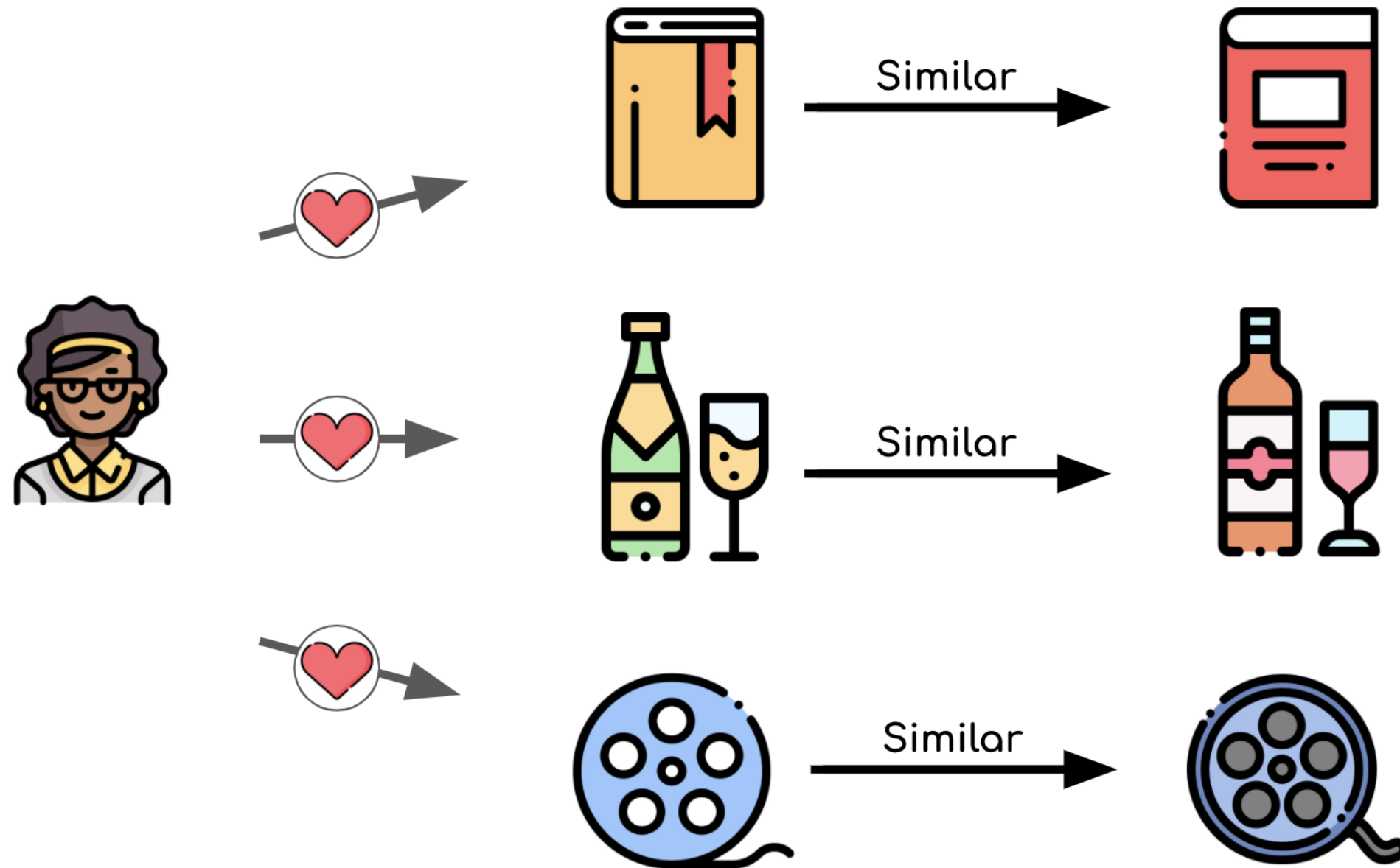
User profile recommendations

BUILDING RECOMMENDATION ENGINES IN PYTHON



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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!

BUILDING RECOMMENDATION ENGINES IN PYTHON