Introduction to Intelligent User Interfaces

Recommender Systems

Recommender Systems

Definition

“Recommender Systems (RSs) are software tools and techniques **providing suggestions for items** to be of use to a user. […] The suggestions relate to various decision-making processes, such as what items to buy, what music to listen to, or what online news to read.” [1, p1]

[1] Francesco Ricci, Lior Rokach and Bracha Shapira. Introduction to Recommender Systems Handbook. In F. Ricci et al. (eds.), Recommender Systems Handbook. Springer Science+Business Media 2011.

Who is in control of your life?

Too Much "Content" for Manual Inspection

The amount of available content is huge, the rate of content creation is high and still increasing, and the majority of content created and shared is of low quality.

- So far, content is mostly real (photos, video, audio)
- We can generate and alter content with AI-Techniques to get more (e.g., GenAI)
- Most content is irrelevant to most people – but sometime very important to a few

Too Much “Content” for Manual Inspection

The amount of available content is huge, the rate of content creation is high and still increasing, and the majority of content created and shared is of low quality.

We need algorithms to make a selection and user interfaces to guide our attention.

Content Selection Dilemma
… random selection of content would not work

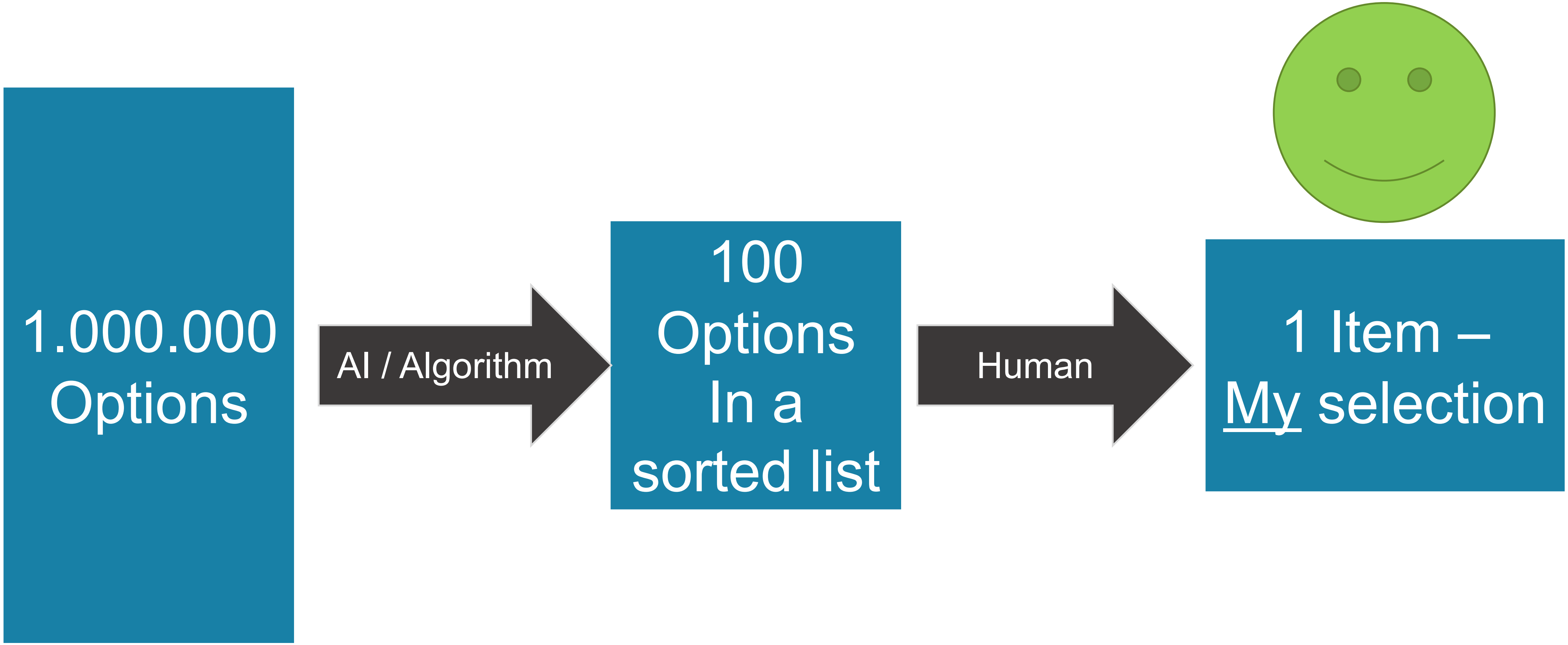
- most of the content is low quality
- not relevant to the user

Random = frustrating experience

- 6 random films Movie-dataset with about 60.000 Movies, e.g.
  - Major Payne (1994),
  - A Down Dirty Shame (1994),
  - The Cowboy Way (1994),
  - Switchblade Sisters (1975),
  - That Old Feeling (1997),
  - Prefontaine (1997)

There is a dilemma:
We cannot consider all options as this would take forever.

Is Human in the Loop the Solution?
Who makes the real decisions?



Feeling in Control is important for the Acceptance of Suggestions

- The interface of **how to present intelligent assistance** to the user is critical for success
- “Users don’t want to be told what to do, they want to choose”
  - Version 1:
    - “take the train at 12:17 from platform 6”
  - Version 2:
    - “which do you want to take? train at 12:17 from platform 6 (takes 45 minutes) or bus at 12:15 from platform 3 (takes 50 minutes, is unreliable)”

Search space and UI are linked!

Search space and UI are linked!

- The reduction of the search space is directly related to
  - the user interface design
  - the modalities available
- Example: shopping
  How many alternatives can you show?
  - voice user interface
  - mobile app
  - laptop screen and mouse
  - 4k screen / wall size display

Convenient and comfortable solutions come at the expense of loosing choice and introducing bias.

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Recommender Systems – Examples?

- How are recommender systems used in these services?
- How do recommender systems impact the user experience?
- What are user **interface patterns** used with recommender systems?

Recommender Systems

- Why are recommender systems used?
- What is the main function?
- What data do recommender systems require?
- How do recommender systems make a user interface intelligent?

Carlos A. Gomez-Uribe and Neil Hunt. 2015. The Netflix Recommender System: Algorithms, Business Value, and Innovation. ACM Trans. Manage. Inf. Syst. 6, 4, Article 13 (December 2015). DOI: https://doi.org/10.1145/2843948

What Book do you Recommend to me?

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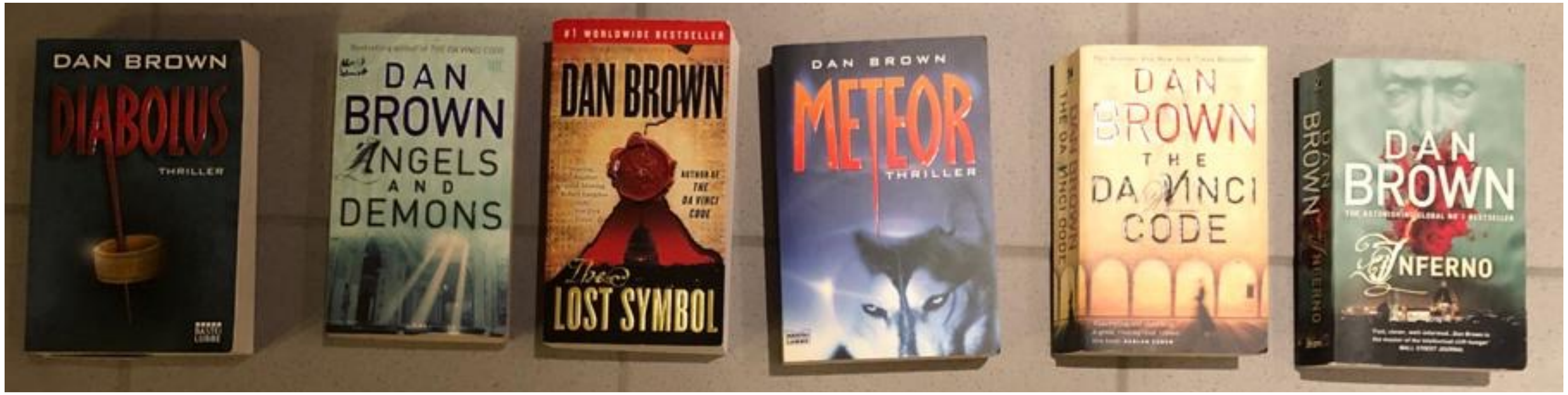
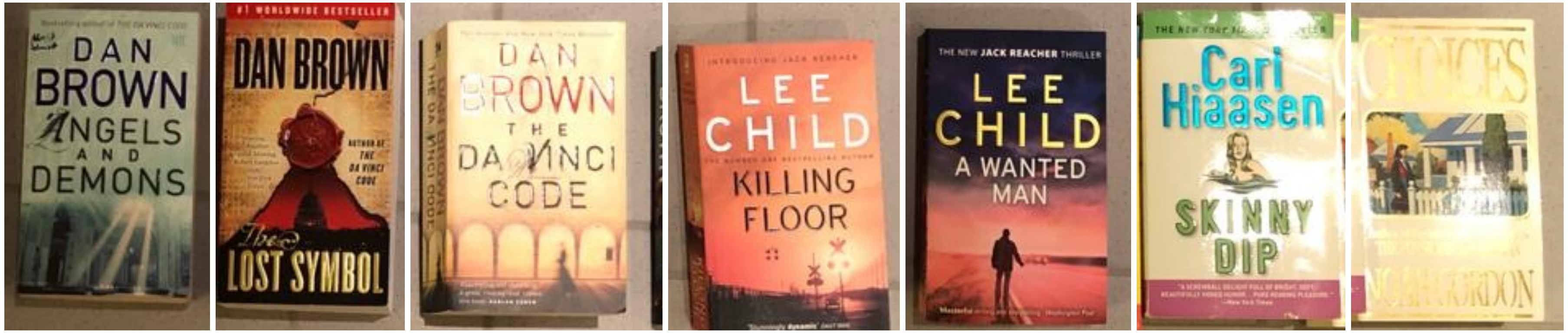
? ?

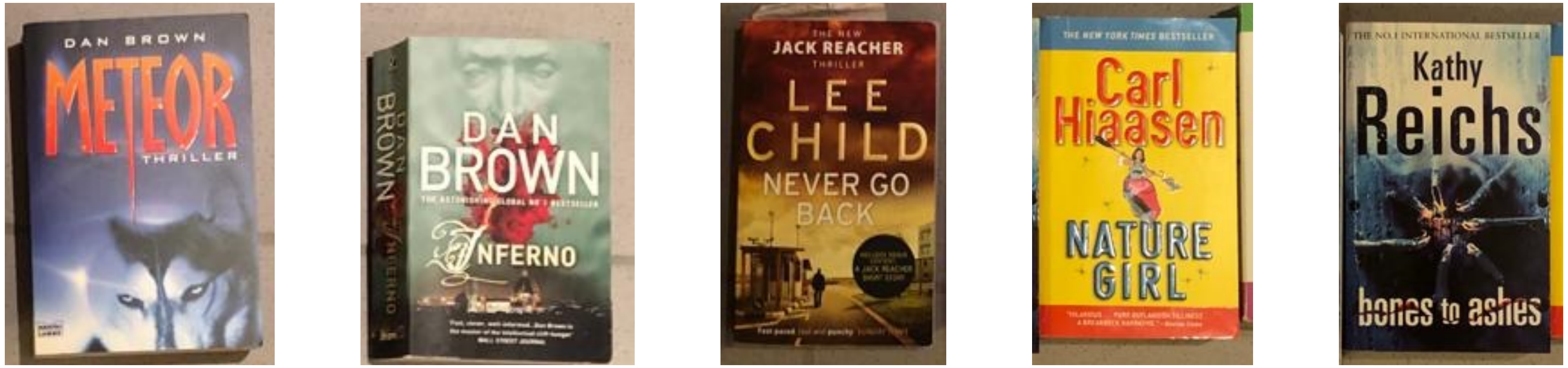
What Book do you Recommend to me?



This is what I read…



Which of these books do you suggest?



Approaches to Recommender Systems

- **Collaborative Filtering**
  “people who liked what you liked also liked X, hence I suggest X to you”
- **Demographics**
  “many people of you age, income, family status, and education like X, hence I suggest X to you”
- **Social Relationships**
  “people you hang out with, your friend, or friend of you friends like X, hence I suggest X to you”
- **Content-based Filtering**
  “X is similar (based on a similarity measure for a domain) to what you liked before, hence I suggest X to you”
- **Contextual**
  “many people in you current situation/context/location like X, as you are in now this context , I suggest X to you”

Approaches to Recommender Systems

Discussion in the context of a dating app

- **Collaborative Filtering**
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Approaches to Recommender Systems

Content-based Filtering

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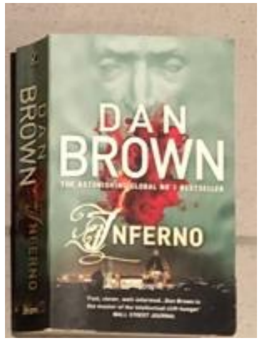
Content Based Filtering

Basic Approach

- What properties / factors / dimensions are describing and discriminating the products?
  → taxonomy, list of dimensions or set of criteria
- Each item can be categorized based on the criteria/dimensions/taxonomy
  → for each item represent how much it matches these criteria in a vector
- How much does the user like products based on the criteria/dimensions/taxonomy?
  → vector for the user that represents their relationship to these criteria
- Identify and recommend items that fit the user's criteria
  → calculate the similarity between item vectors
  and user vectors



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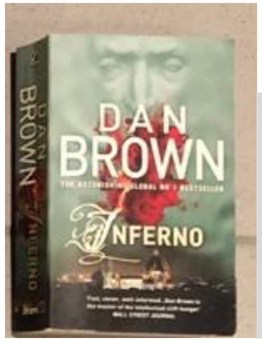
Semantics are required!



Language, genre, time set, main characters, location/setting, theme, length, time written, number of parallel plots, language complexity,…

Approaches to Recommender Systems

Collaborative Filtering

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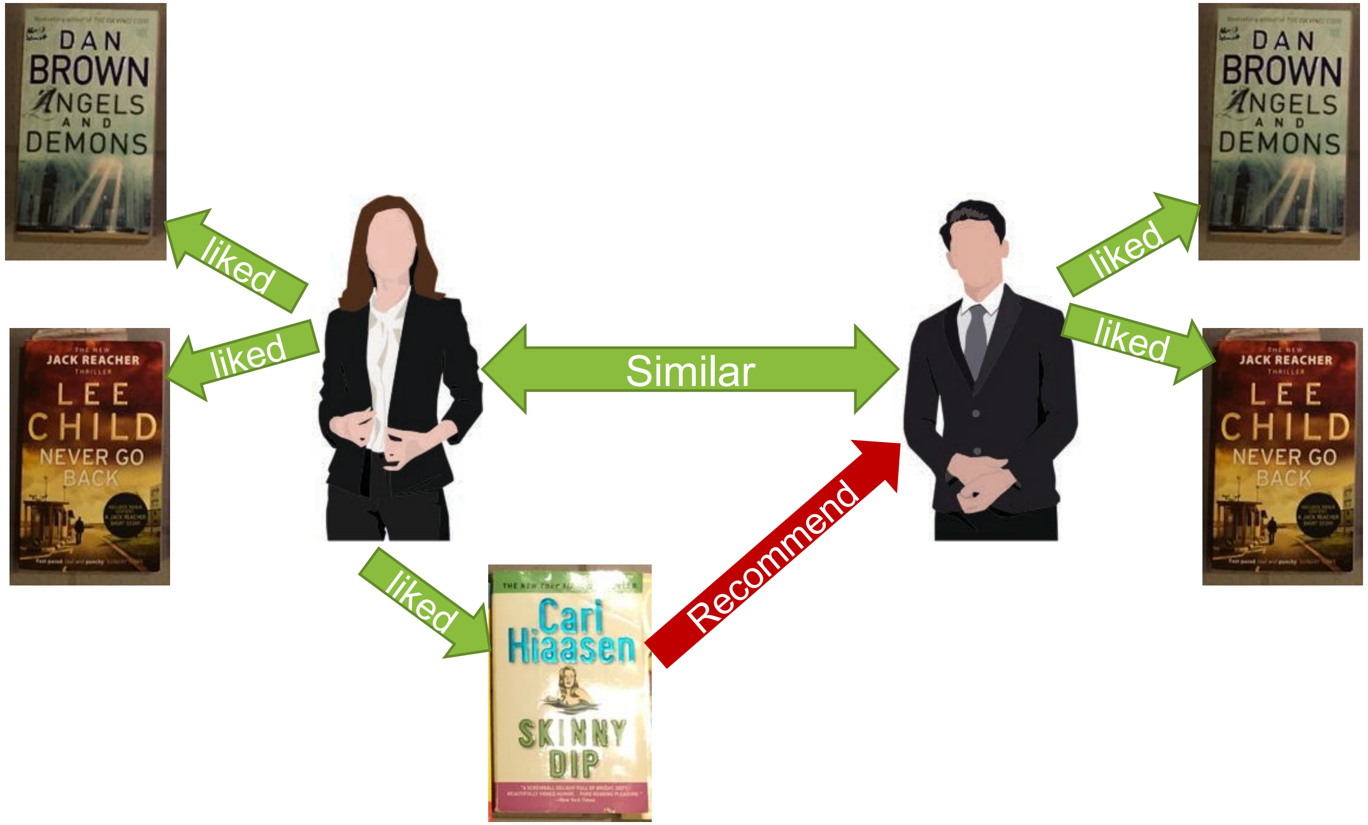
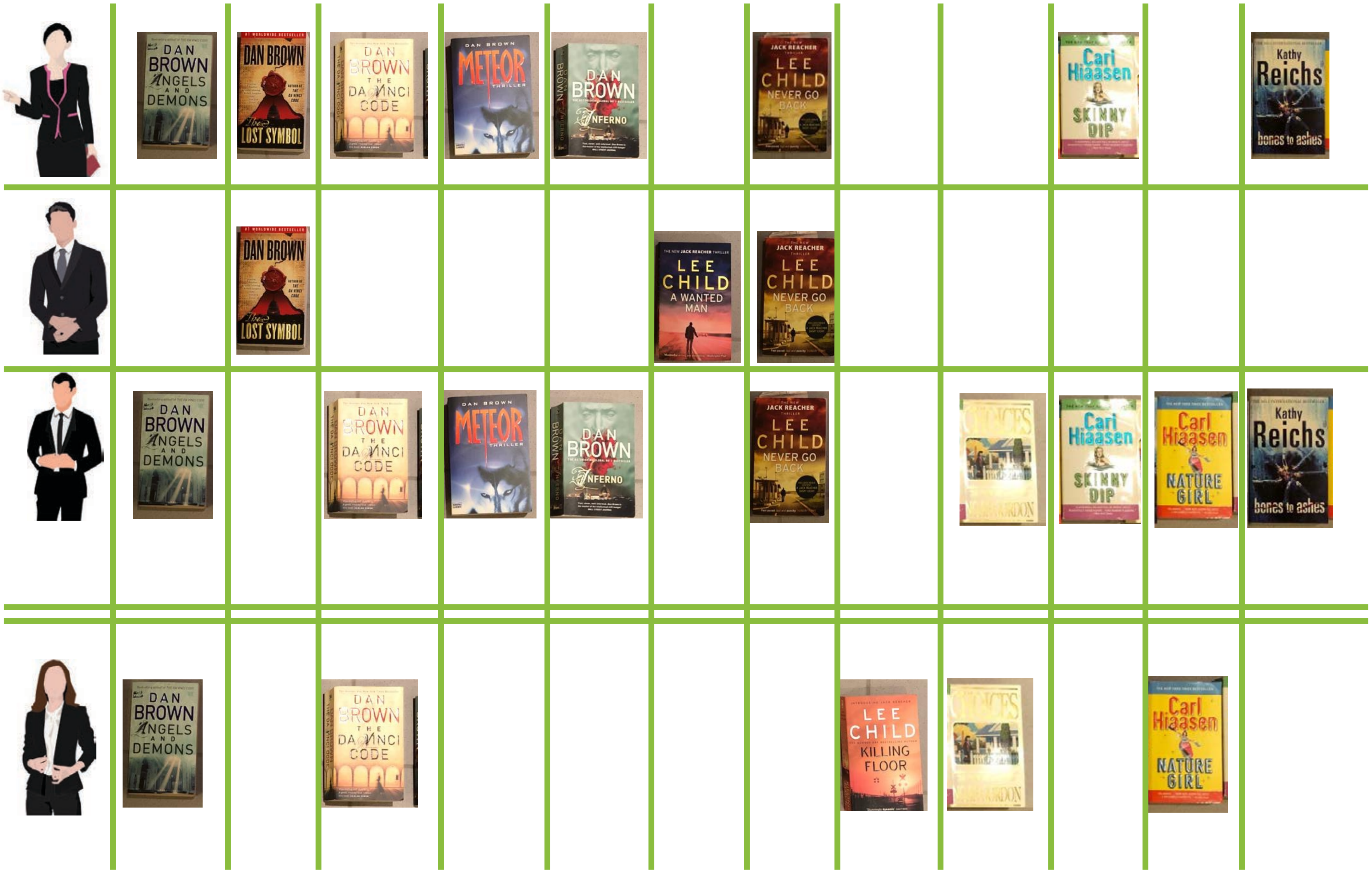
Idea of User Based Collaborative Filtering

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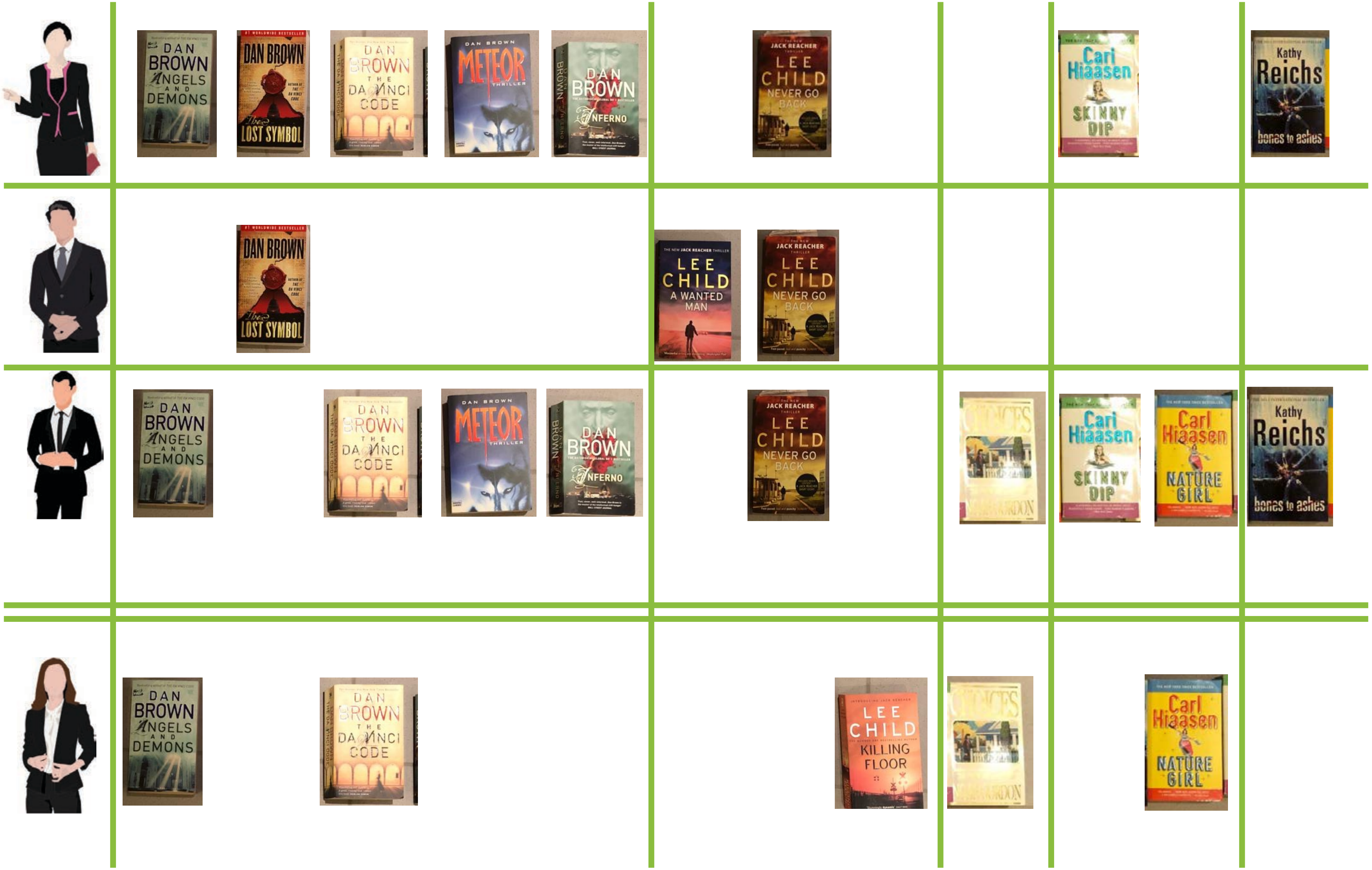
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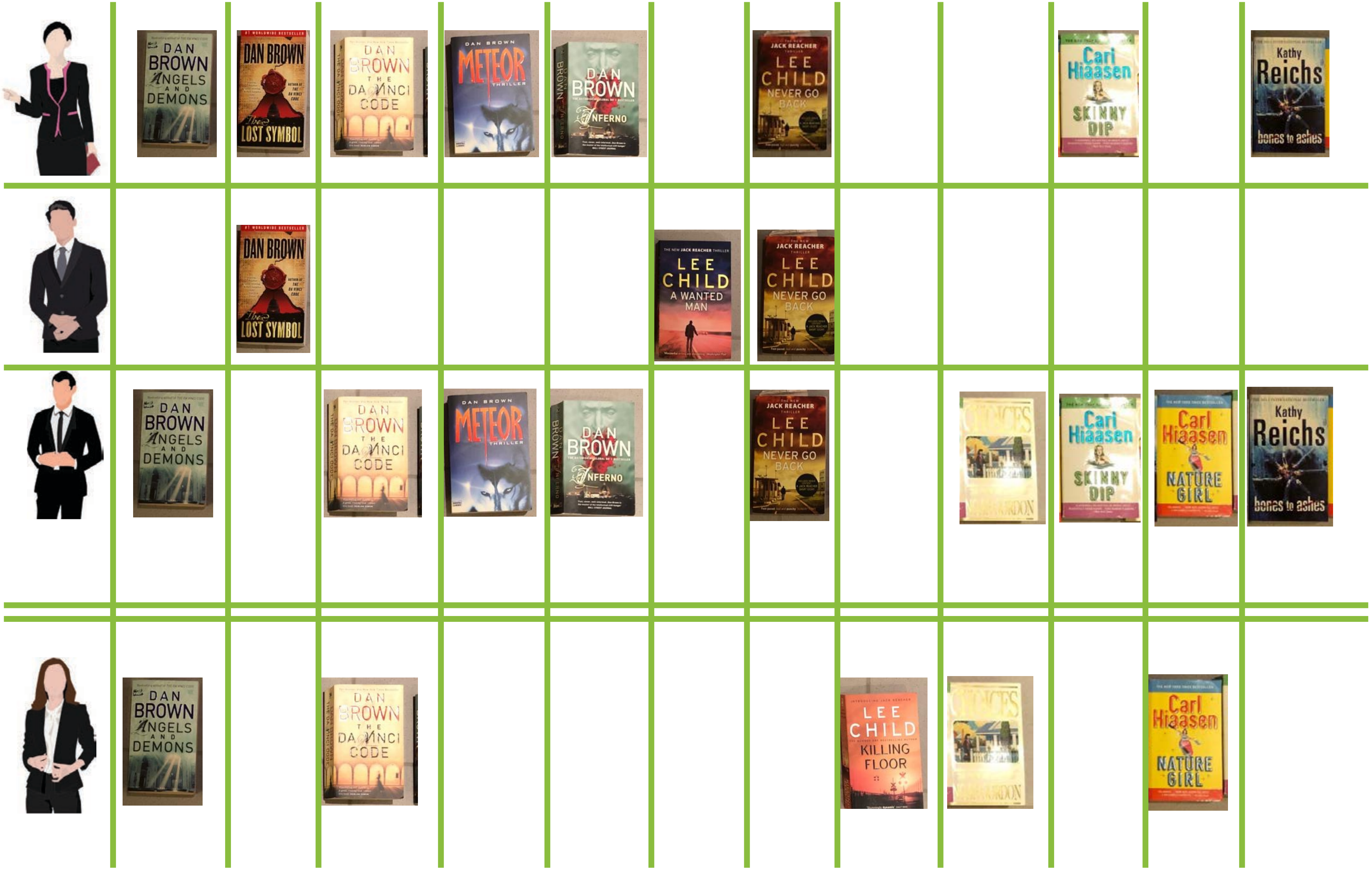
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	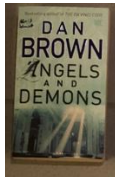	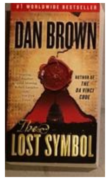	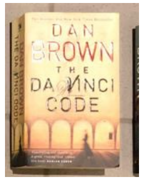	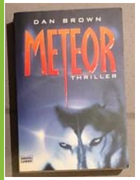	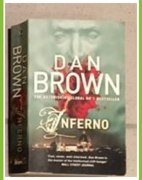	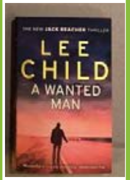	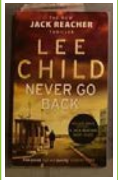	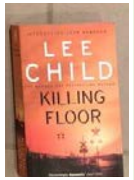	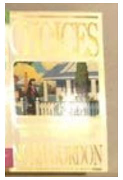	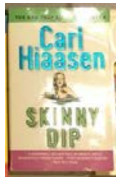	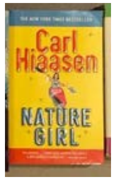	
	8	7	9	4	9		10			4		7
		2				6	9					
	4		6	10	8		9		6	7	9	8
	4	?	6	?	?	?	?	9	5	?	10	?

	Item1	item2	item3	item4	Item5	item6	item7	item8	Item9	item10	item11	item12
u1	8	7	9	4	9		10			4		7
u2		2				6	9					
u3	4		6	10	8		9		6	7	9	8
u4	4	?	6	?	?	?	?	9	5	?	10	?

Discussion – How to get item ratings?

Explicitly and Implicitly

- Scenario 1: Web-based reading platform/library
- Scenario 2: Dating app
- Scenario 3: Restaurant Finder app

What do you get ratings for? What is the item?

What relevant questions can you ask to get item ratings?

How do you get implicit ratings from “automated observation”?

Recommender Systems – Getting user data

What are ways to get data from the user for recommender systems?

- Explicit:
  - Questionnaires at setup time
  - Ratings of items
  - Feedback questions
- Implicit
  - Using items (e.g. watching a movie, listen to music, putting something on a watch list, buying a book)
  - Sharing items (e.g. recommending an article, retweets)
  - Removing items (e.g. deleting a playlist, skipping a suggested song)

Collaborative Filtering

Basic Approach

- Tables:
  - User, Item, Rating
  - Item, Item description
- Approach
  - Users rate items (implicitly, explicitly), e.g., like movie, buy book, recommend hotel…

    → Table: user, item, rating
  - Compute similarity between users (or between items)

    → set of users (or set of items) that is similar to the user
    (the item) we create a recommendation for
  - Predict items (new to the target user) based on the information of similar users

    → weighted list of recommendations

Calculating the similarity

How similar are user to each other?

- Calculating the difference between rating vectors, e.g., k-nearest neighbor, Euclidian distance, Pearson correlation, Cosine distance

	Item A	Item B	Item C	Item D	Cosine Similarity(Ui,Ux)
User 1	7	10	3	4	0,938088
User 2	7	8	5	3	0,948847
User 3	8	2	5	3	0,708337
User 4	2	9	5	2	0,986921
User 5	1	2	5	2	0,828970
User X	3	8	5	3	1,000000

$$\text{similarity} = \cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\|\|\mathbf{B}\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}}$$

https://en.wikipedia.org/wiki/Cosine_similarity

Example based on:
https://buddingdatascientist.wordpress.com/2017/03/22/how-to-calculate-cosine-similarity-in-excel/

Heuristic required for tables with missing values!

Assessing Similarity?

How could Machine Learning play a role here?

	8	7	9	4	9		10			4		7
		2				6	9					
	4		6	10	8		9		6	7	9	8
	4	?	6	?	?	?	?	9	5	?	10	?

	Item A	*Item B*	*Item C*	*Item D*	*Cosine Similarity(Ui,Ux)*
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Predicting the right item?

Example Similarity Matrix

Similarities are NOT calculated – for illustration only

8	7	9	4	9		10			4		7
	2				6	9					
4		6	10	8		9		6	7	9	8
4	?	6	?	?	?	?	9	5	?	10	?

Similarity Matrix (illustration example – not calculated)

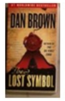
0.4
0.7
0.9
1

Based on https://medium.com/swlh/how-to-build-simple-recommender-systems-in-python-647e5bcd78bd

Predicting the right item? Using Weighted Rating Matrix

Recommender Systems

Rating Matrix (part)

		
	7	4
	2	
		10
	?	?

*

*

*

Similarity Matrix

	0.4
	0.7
	0.9
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Predicting the right item? Using Weighted Rating Matrix

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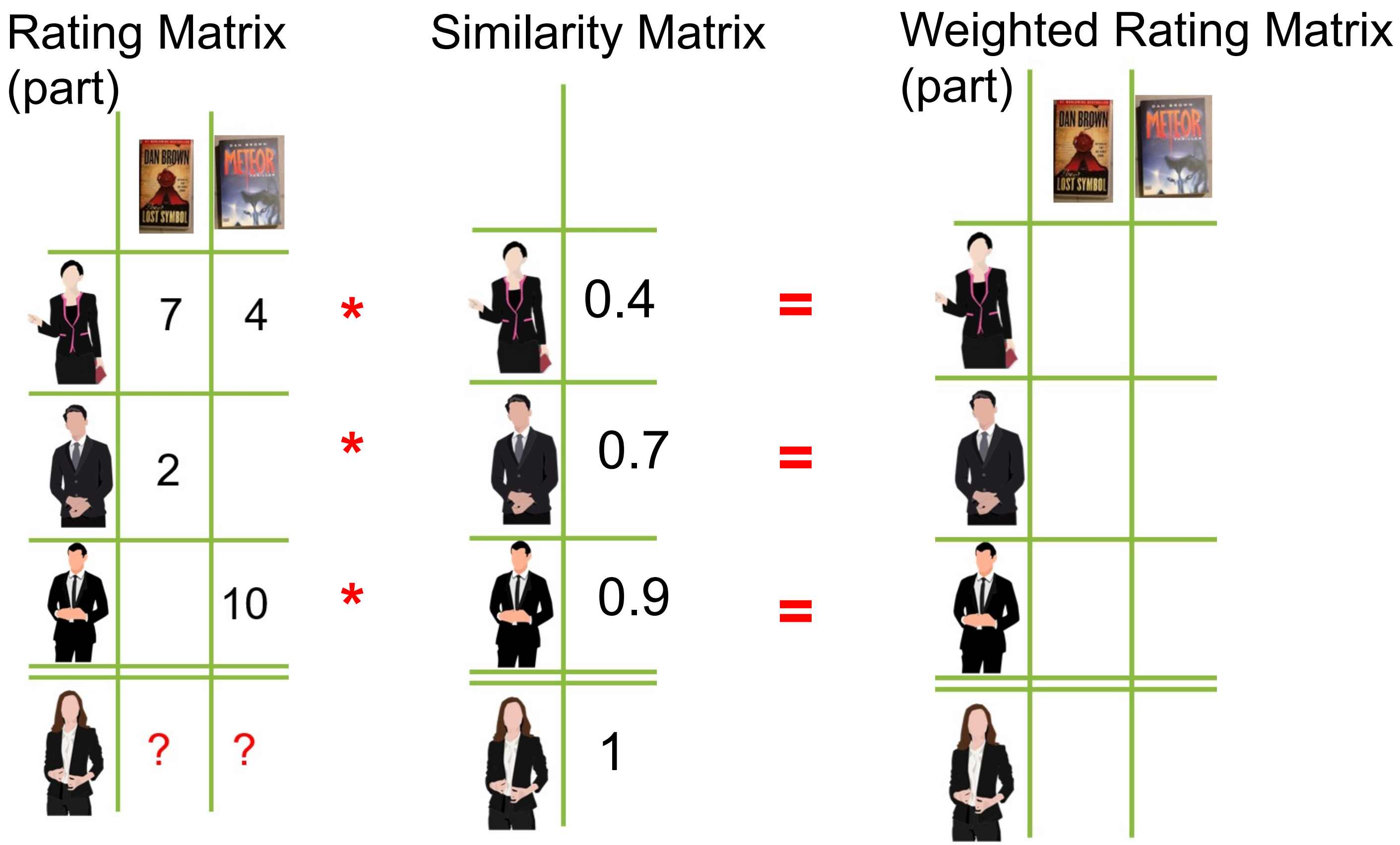

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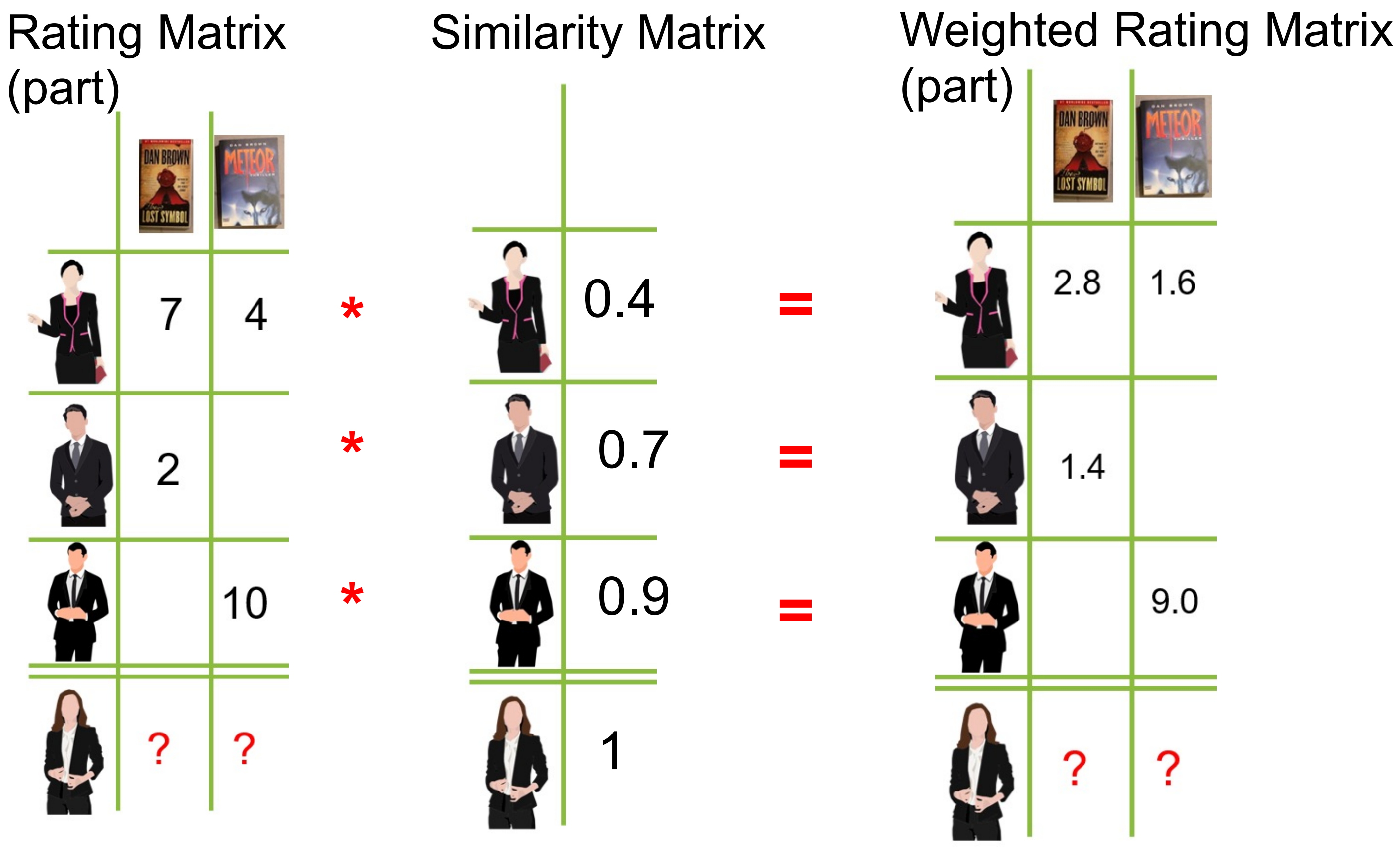
Predicting the right item? Using Weighted Rating Matrix

Recommender Systems



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Predicting the right item? Using Weighted Rating Matrix

Recommender Systems

Weighted Rating Matrix
(part)

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Predicting the right item? Using Weighted Rating Matrix

Recommender Systems

Weighted Rating Matrix
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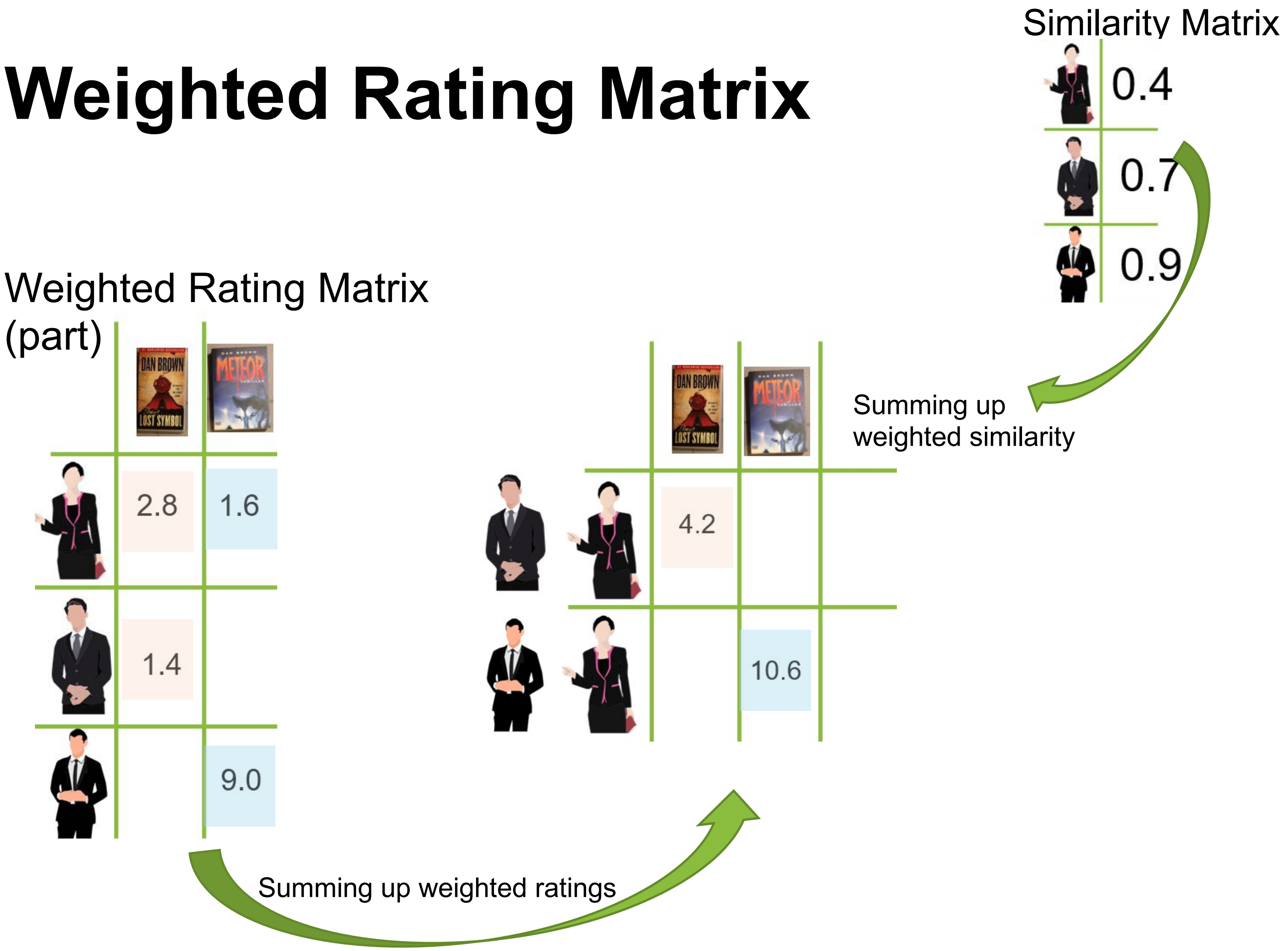
Weighted Rating Matrix



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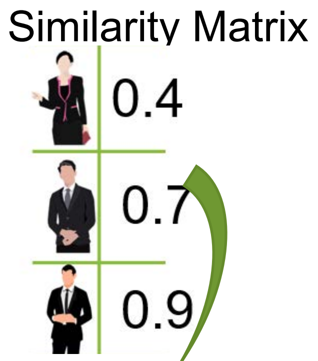
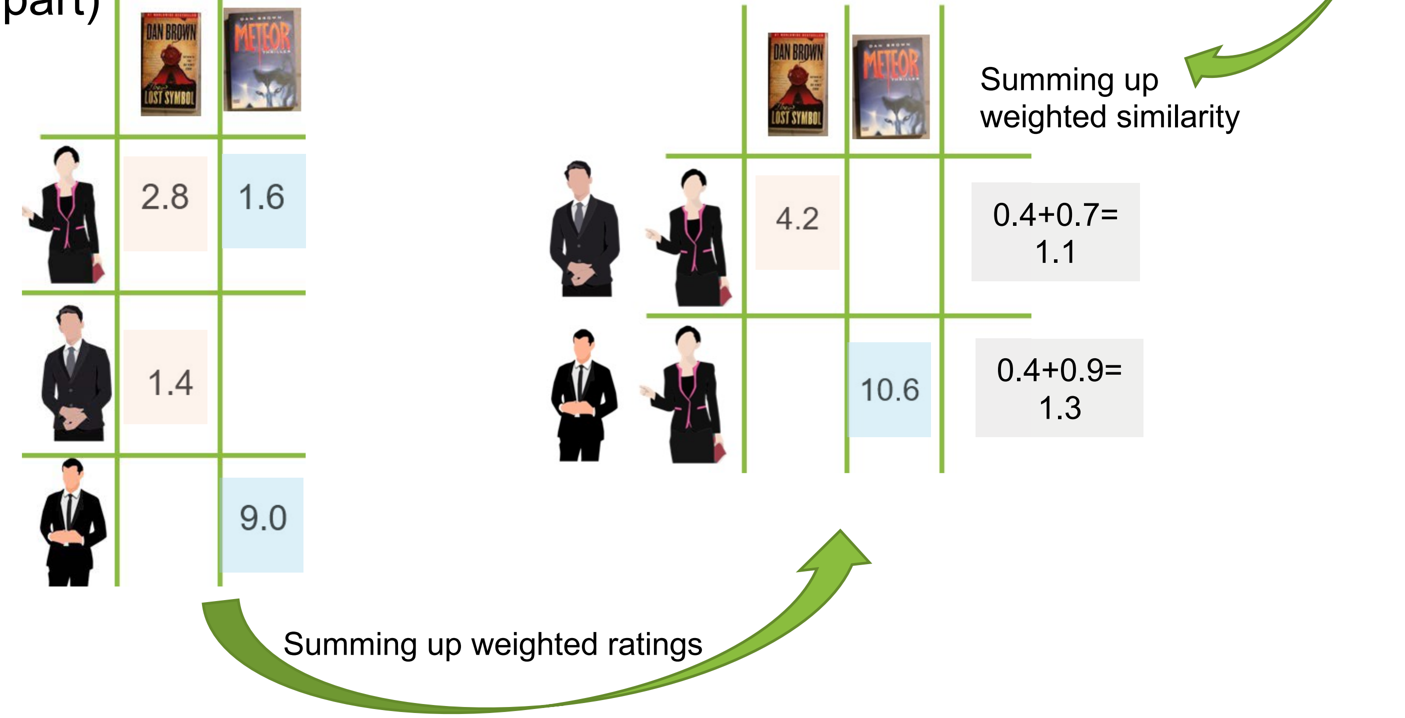
Weighted Rating Matrix

Recommender Systems



Weighted Rating Matrix
(part)



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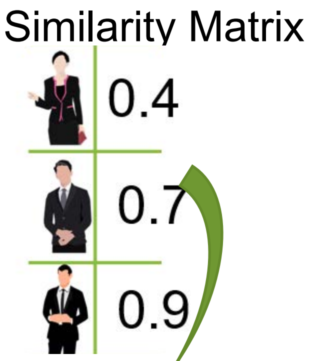

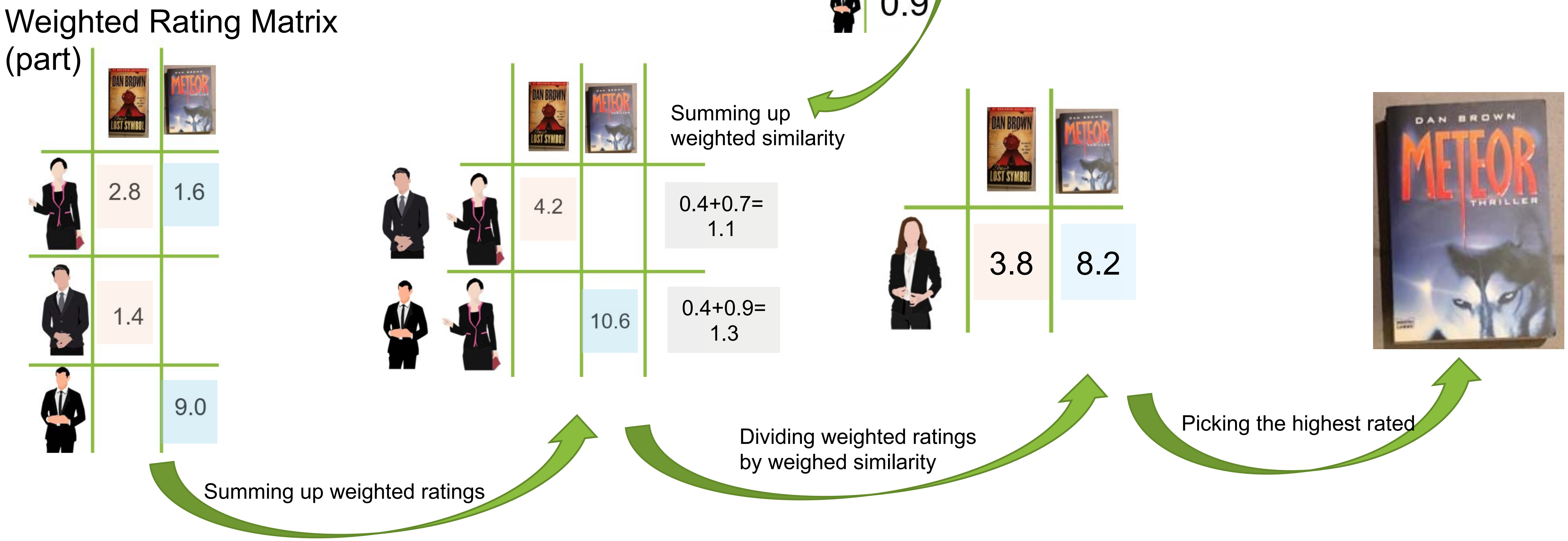

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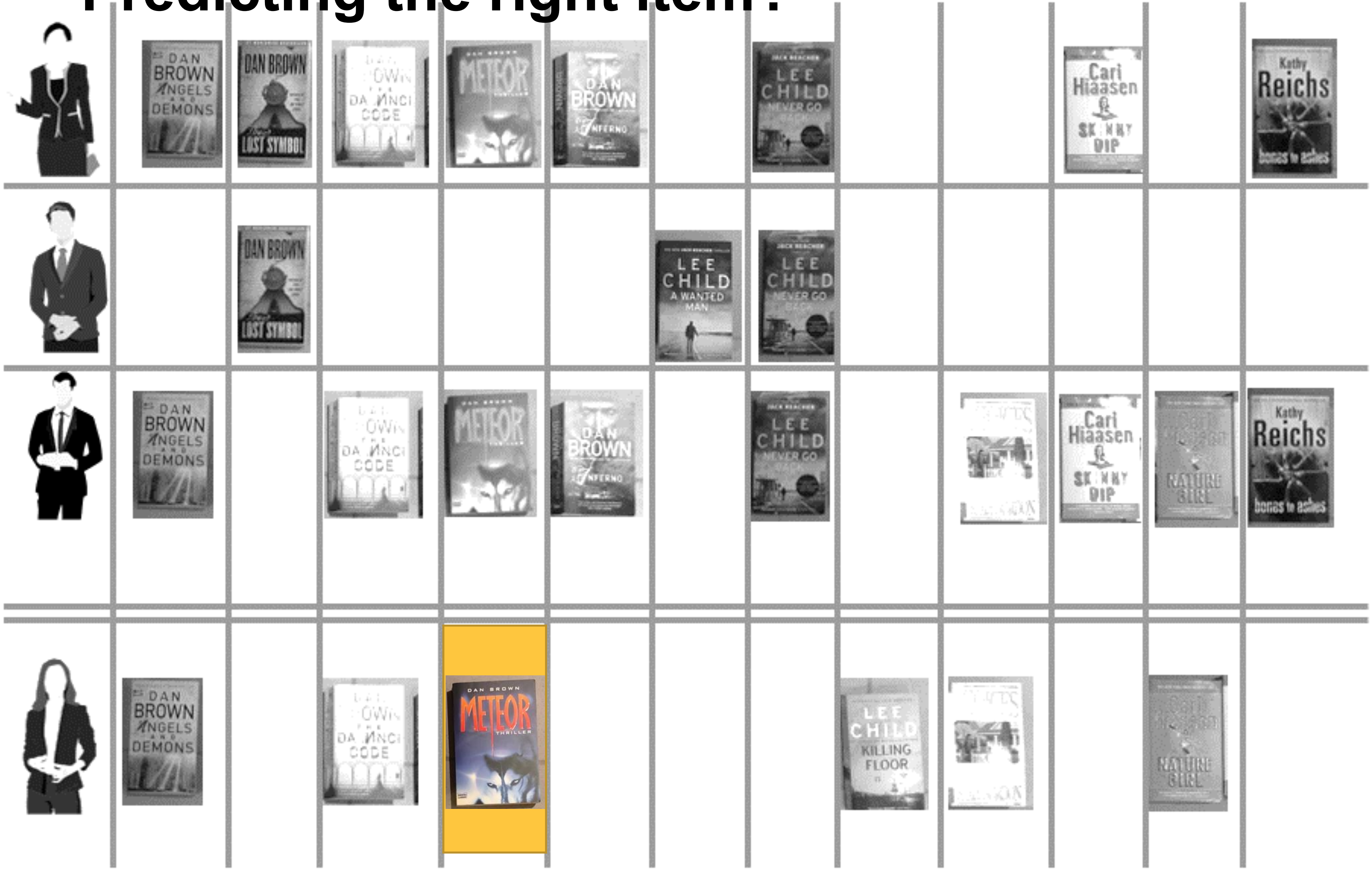
Predicting the right item?



Collaborative Filtering

User Based

- Calculate the similarity between users
- Suggest items that similar users liked

Item Based

- Calculate the similarity between items based on user ratings – **no semantics are required!**
- Suggest an item that is similar (with respect to metadata, e.g., ratings) to an item the user already likes

Cold-Start Problem

What is n

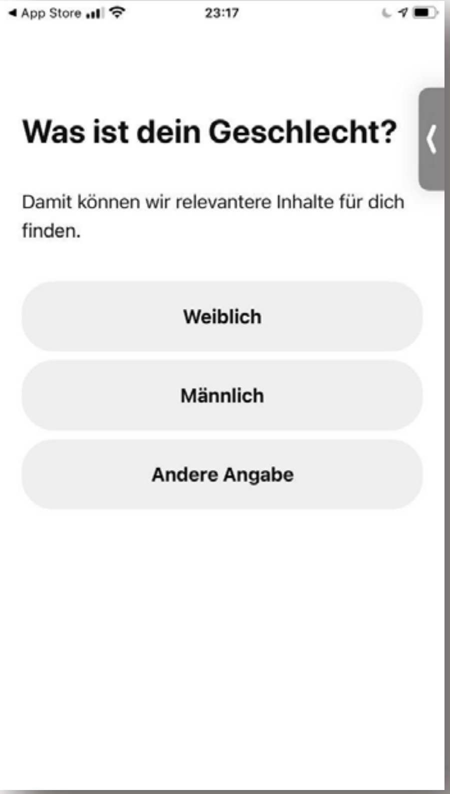
- **Basic problem: as a system is created data is missing. The algorithms need initial information (e.g. to calculate similarities).**
- **What could be new? What is the problem?**
  - **User**: no information yet, no recorded interaction nor know preferences
  - **Item**: the item has not been “like” or viewed by anyone yet, no knowledge who may like it or how its rating are similar
  - **Community**: new system is created, lack of information about users as well as item
- **Solutions?**
  - Hybrid approaches (e.g. using content based filtering to get started and then move more towards collaborative filtering)
  - Use social, demographics, context, content to get started
  - Require initial interaction (e.g. questionnaire, ask for examples, …)

[1] Bobadilla, Jesús; Ortega, Fernando; Hernando, Antonio; Bernal, Jesús (February 2012). "A collaborative filtering approach to mitigate the new user cold start problem". Knowledge-Based Systems. doi:10.1016/j.knosys.2011.07.021.
[2] https://en.wikipedia.org/wiki/Cold_start_(recommender_systems)

Pinterest

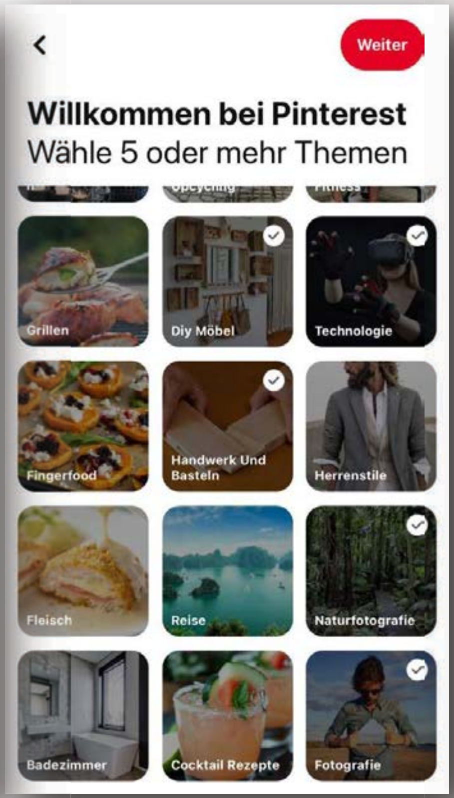
Registration Process and start-up

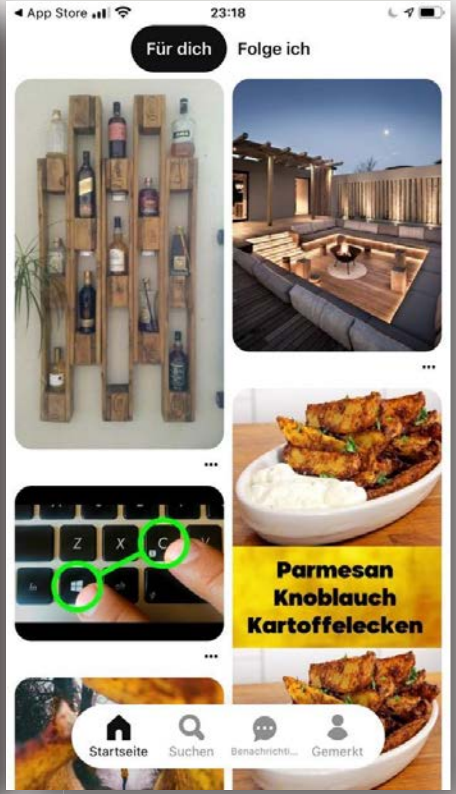
Demographics



Contextual

Explicit Interest





How to include new item?

Scenario: News Feed

- You create a recommender system for a news feed in social media (e.g. twitter style).
- How do you add new articles?
- Assuming you get a lot of articles….

Sparseness of Ratings

- E.g. Amazon (low estimates for illustration only)
  - Over 10 Million products
  - Over 100 Million customer

- What is the problem?

What Book do you Recommend to me?
Why does the UI matter?

Recommender Systems – Summary

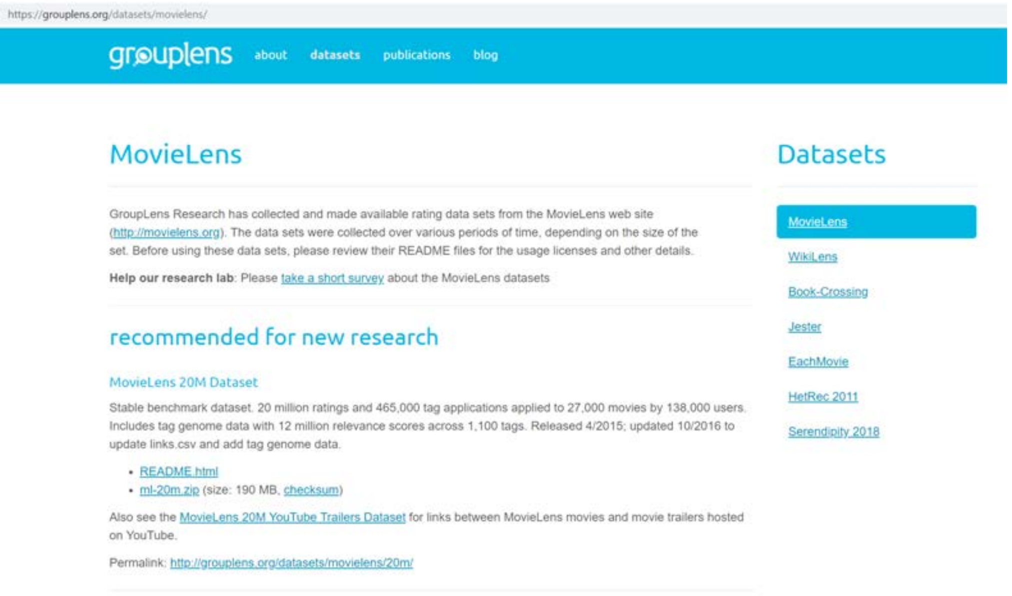
Content-based Filtering

- Based on the similarity of items
- How similar is a new item to an item already liked/watched/bought by the user
- Advantage
  - If similarity is known or can be calculated, no ratings/actions from the user are required
- Difficulty:
  - Information/meta-data/algorithms for calculating similarity are required

Collaborative Filtering

- suggestions are made based on users that had similar interests/actions
- How has a similar user liked this item?
- Advantage:
  - Know knowledge about the item is required, no meta data or similarity calculation of items required
- Difficulty:
  - Data about other users is required
  - “cold-start” problem

Example data for experiments



https://grouplens.org/datasets/movielens/

	A	B	C	D	E
1	userId	movieId	rating	timestamp	
2	1	1	4	964982703	
3	1	3	4	964981247	
4	1	6	4	964982224	
5	1	47	5	964983815	
6	1	50	5	964982931	
7	1	70	3	964982400	
8	1	101	5	964980868	
9	1	110	4	964982176	
10	1	151	5	964984041	
11	1	157	5	964984100	
12	1	163	5	964983650	
13	1	216	5	964981208	
14	1	223	3	964980985	
15	1	231	5	964981179	
16	1	235	4	964980908	
17	1	260	5	964981680	
18	1	296	3	964982967	
19	1	316	3	964982310	
20	1	333	5	964981179	
21	1	349	4	964982563	
22	1	356	4	964980962	
23	1	362	5	964982588	
24	1	367	4	964981710	
25	1	423	3	964982363	

Additional reading material: https://hub.packtpub.com/recommending-movies-scale-python/

Live coding example

IUI - Recommendation Systems - Collaborative Filtering

by Sven Mayer

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

Download and extract dataset

Source https://grouplens.org/datasets/movielens/

In [ ]:
```
# Download
import urllib.request
url = 'http://files.grouplens.org/datasets/movielens/ml-latest-small.zip'
urllib.request.urlretrieve(url, './archive.zip')

# Extract
import zipfile
with zipfile.ZipFile("./archive.zip","r") as zip_ref:
    zip_ref.extractall("")

import os
os.rename("ml-latest-small", "archive")
```

In [ ]:
```
! ls -la -h archive
```

In [ ]:
```
dfRatings = pd.read_csv("./archive/ratings.csv")
dfRatings.head()
```

In [ ]:
```
print("%i Ratings" % len(dfRatings))
```

Examples for recommender systems in Python

https://www.youtube.com/watch?v=z0dx-YckFko

- https://kerpanic.wordpress.com/2018/03/26/a-gentle-guide-to-recommender-systems-with-surprise/
- https://www.analyticsvidhya.com/blog/2016/06/quick-guide-build-recommendation-engine-python/
- https://medium.com/@connectwithghosh/recommender-system-on-the-movielens-using-an-autoencoder-using-tensorflow-in-python-f13d3e8d600d

Algorithms for Recommender System

- Not core to Intelligent User Interfaces
- Efficient implementations in libraries
- Important to understand the algorithms to get the parameters right

- Introductory video https://www.youtube.com/watch?v=Eeg1DEeWUjA

Summary

- Content-based Filtering
- Collaborative Filtering
  - User Based
  - Item Based
- Cold-Start Problem
- UI Implications

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