PARIS LODRON UNIVERSITY SALZBURG

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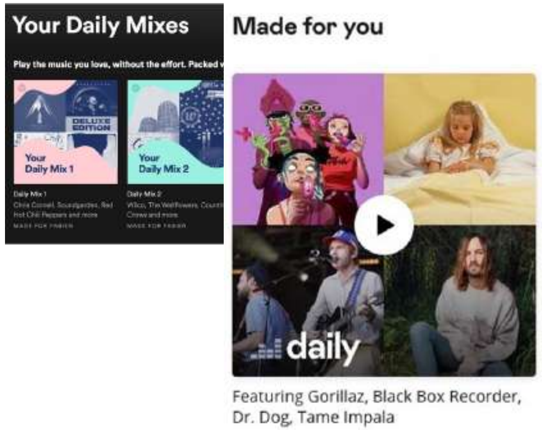
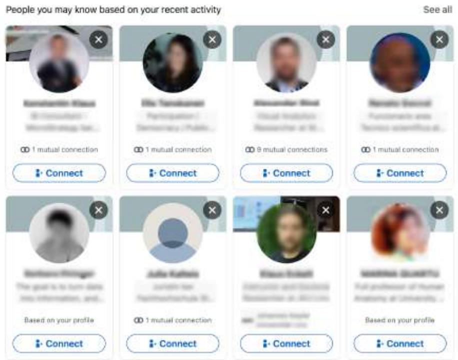
Recommender Systems 1

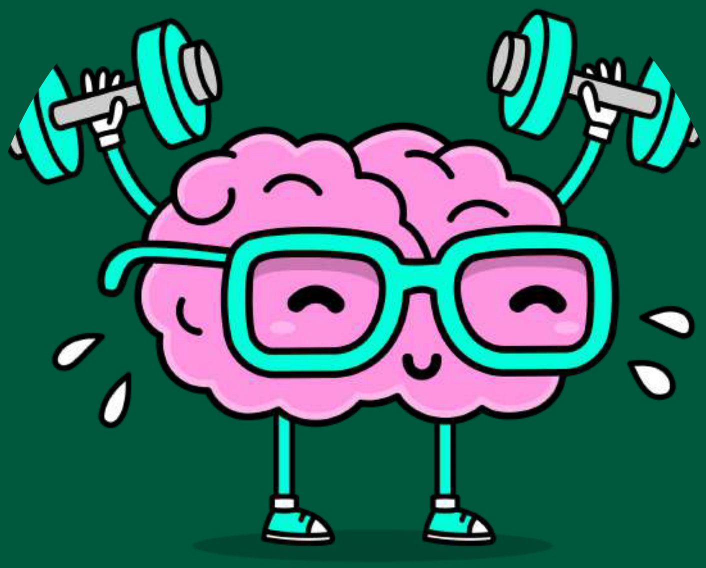
Day 1

Example: Recommender systems

- To which degree do you rely on recommender systems?
- How do recommender systems work?
- Which data do they need?

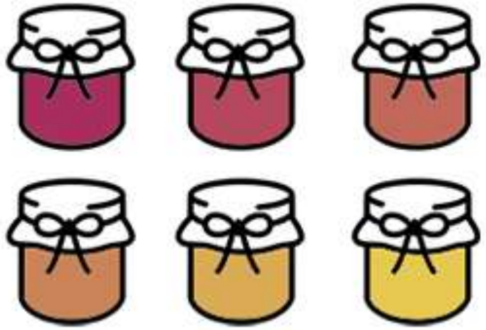






Motivation—why recommender systems?

Seminal example



Is the goal
to increase sales?

Is the goal
to have
an attractive offer?

higher purchase satisfaction

attracted 40% of shoppers

30% sales

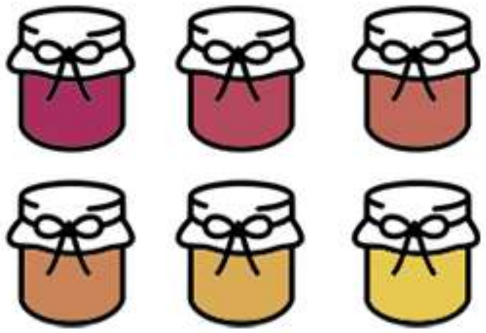
attracted 60% of shoppers

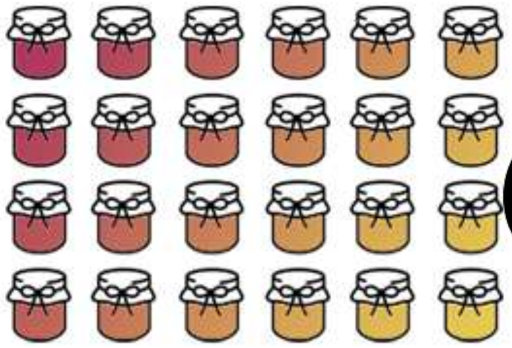
3% sales

Iyengar, S. S., & Lepper, M. R. (2000). When choice is demotivating: Can one desire too much of a good thing?. Journal of personality and social psychology, 79(6), 995.

Schwartz, B. (2004). The paradox of choice: Why more is less. New York: Ecco. http://www.yourmarketingrules.com/the-paradox-of-choice/

Seminal example





Is the goal to increase sales?

Is the goal to have an attractive offer?

higher purchase satisfaction

less attractive

30% sales

more attractive

3% sales

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Information Overload—Choice Overload—How do I find the right element?

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Information and choice overload—
Two interrelated problems

- originates in information theory
- exposure to or provision of *too much* information (or data)
- humans have fairly limited cognitive processing capacity
- thus,
  with information overload, it is likely that decision quality decreases

We need to filter information.

Information curation (also called content curation)

carried out (manually) by specially designated curators

e.g.,

- museums and galleries have curators to select items for collection and display
- music labels select artists (and songs) that are recorded and marketed
- DJs of radio stations select songs to be played on air
- journalists research, filter, and select the information that is communicated to the public

Algorithmic curation

**the automatic
selection, organizing, and presenting
of content**

Why using recommender systems?

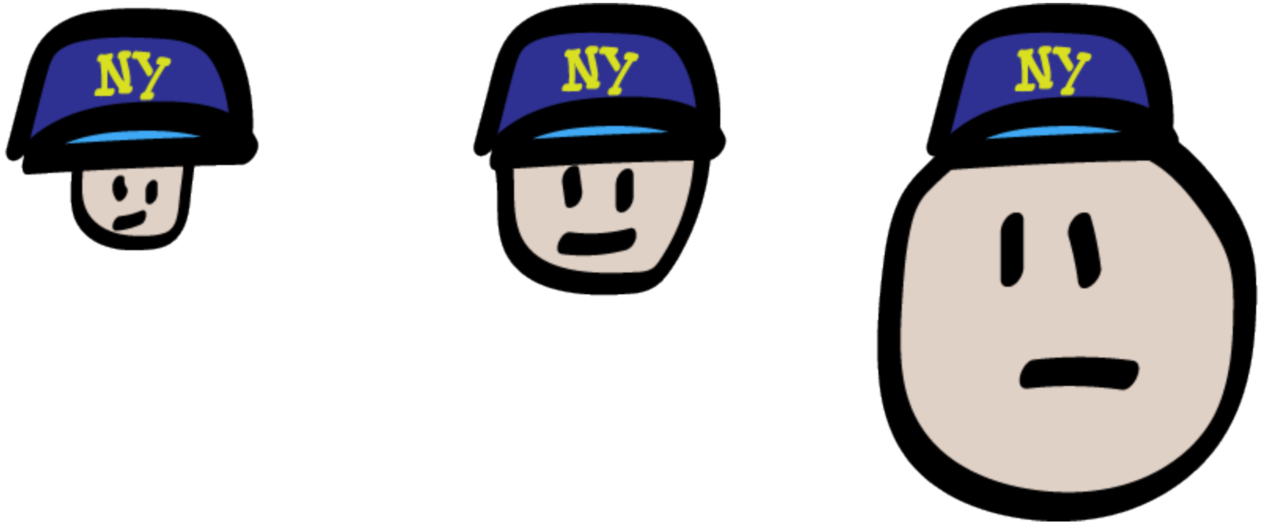
Value for the consumer

- Find things that are interesting
- Narrow down the set of choices
- Help explore the space of options
- Discover new things
- ...

Value for the provider

- Additional service for the customer
- Increase customer loyalty
- Increase sales, click-through rates, conversion, etc.
- Opportunities for promotion, persuasion
- ...

One size does not fit all.



Espen Klem, https://www.flickr.com/photos/eklem/24352287640

It is not all about the person—(also) the situation matters.

depends on the person	depends on the situation

https://marketinginsidergroup.com/wp-content/uploads/2016/06/150-People.jpg

1000/0*ne9Fr33kmEjJ2pGw.jpg

In short:
Motivation for (personalized) recommendation

information and choice overload

individual needs and demands

situational needs and demands

We need the 'right' information,
at the 'right' time,
in the 'right' place,
in the 'right' way,
to the 'right' person.

Gerhard Fischer (2012)—and many others

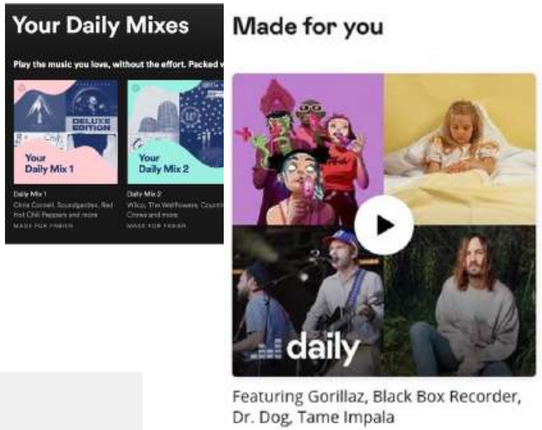
Gerhard Fischer (2012). Context-aware systems: the "right" information, at the "right" time, in the "right" place, in the "right" way, to the "right" person. In Proceedings of the International Working Conference on Advanced Visual Interfaces (AVI '12), pp 287–294. DOI: 10.1145/2254556.2254611

Recommender systems

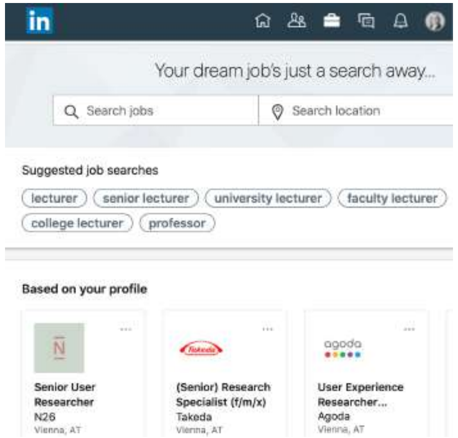
We encounter recommender systems on a daily basis.

e-commerce sites

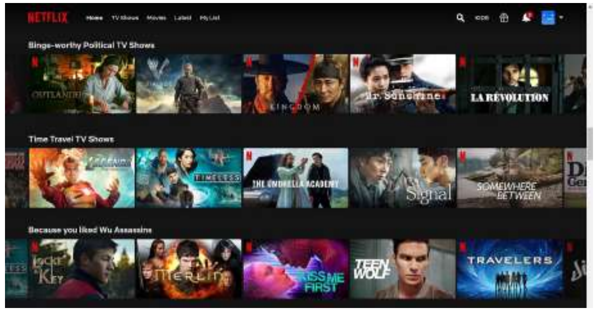
music platforms



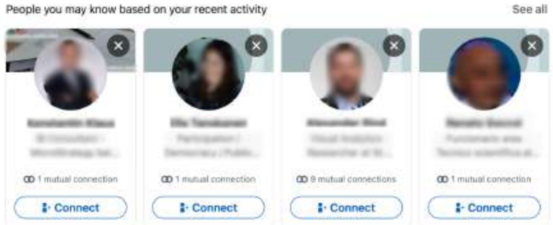
job platforms



movies



social media



Definition—Problem domain

Recommendation systems (RS) help to match users with items to:

- Ease information overload
- Sales assistance (e.g., guidance, advisory, persuasion)

"RS are software agents that elicit the interests and preferences of individual consumers [...] and make recommendations accordingly.
They have the potential to support and improve the quality of the decisions consumers make while searching for and selecting products online."

Xiao, Bo, and Izak Benbasat. "E-commerce product recommendation agents: Use, characteristics, and impact." MIS quarterly (2007): 137-209.

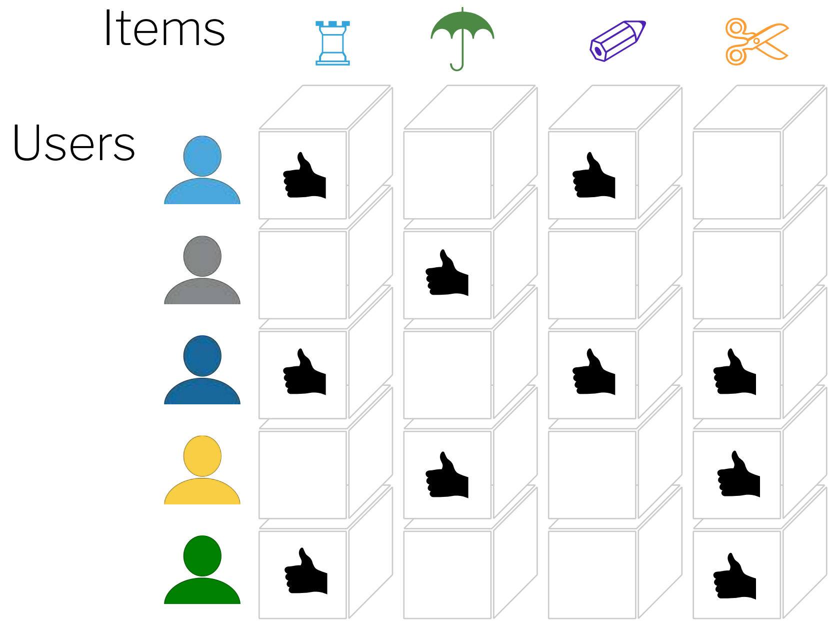
Recommendation as a matrix completion problem

- Two-dimensional matrix of ratings organized by user and item
- Typically a sparse matrix
- Prediction problem:
  Interpolate ratings that are not present in the original matrix

user x item → rating

$$f : U \ x \ I \rightarrow \mathcal{R}$$

Goal: predict what people will like — based on what they have liked



Interactions are observed in data.

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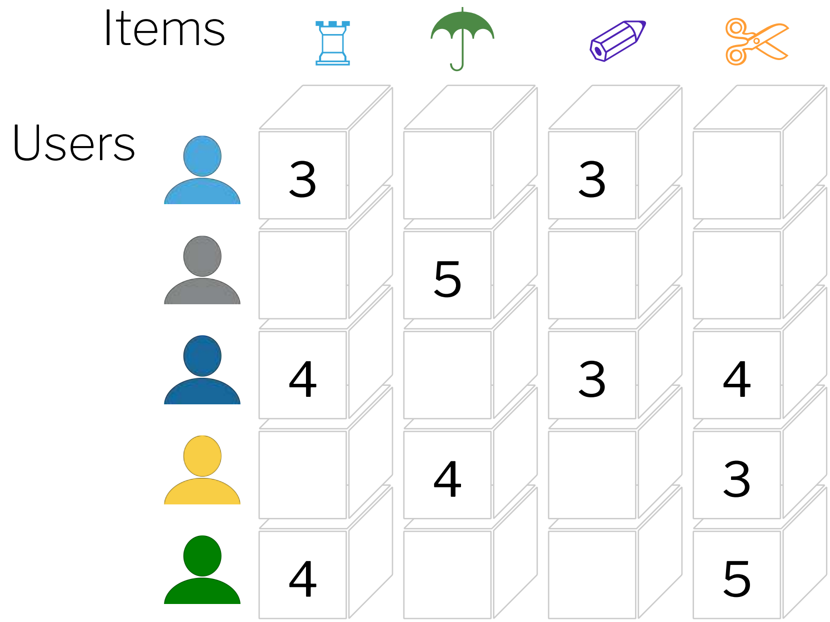


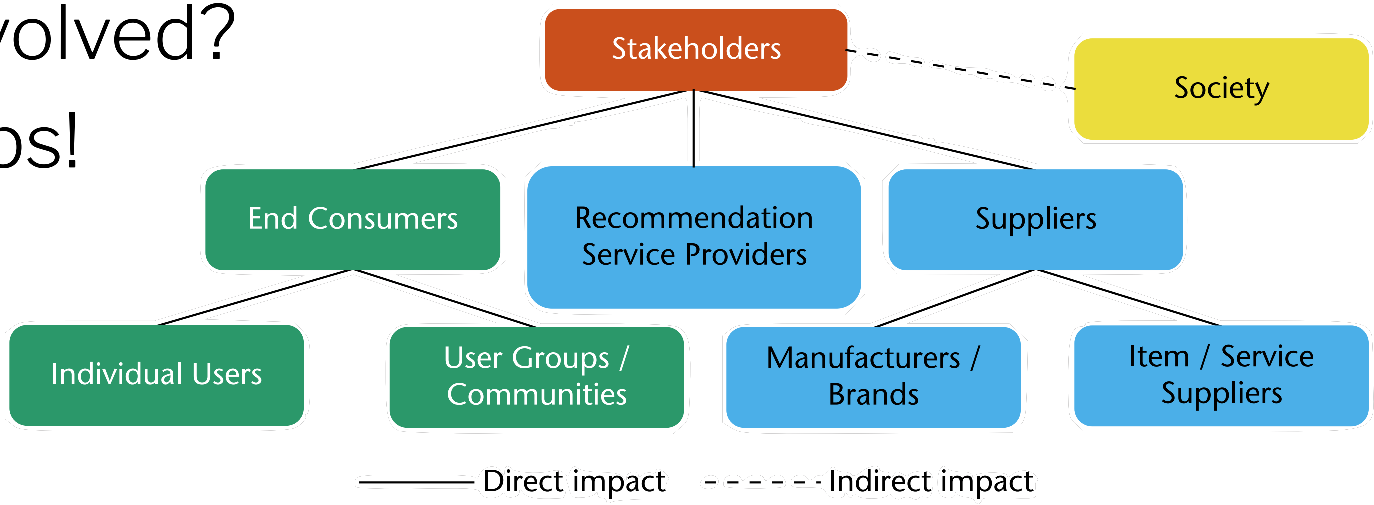
Interactions are observed in data.

Functions of recommender systems

Stakeholders of recommender systems

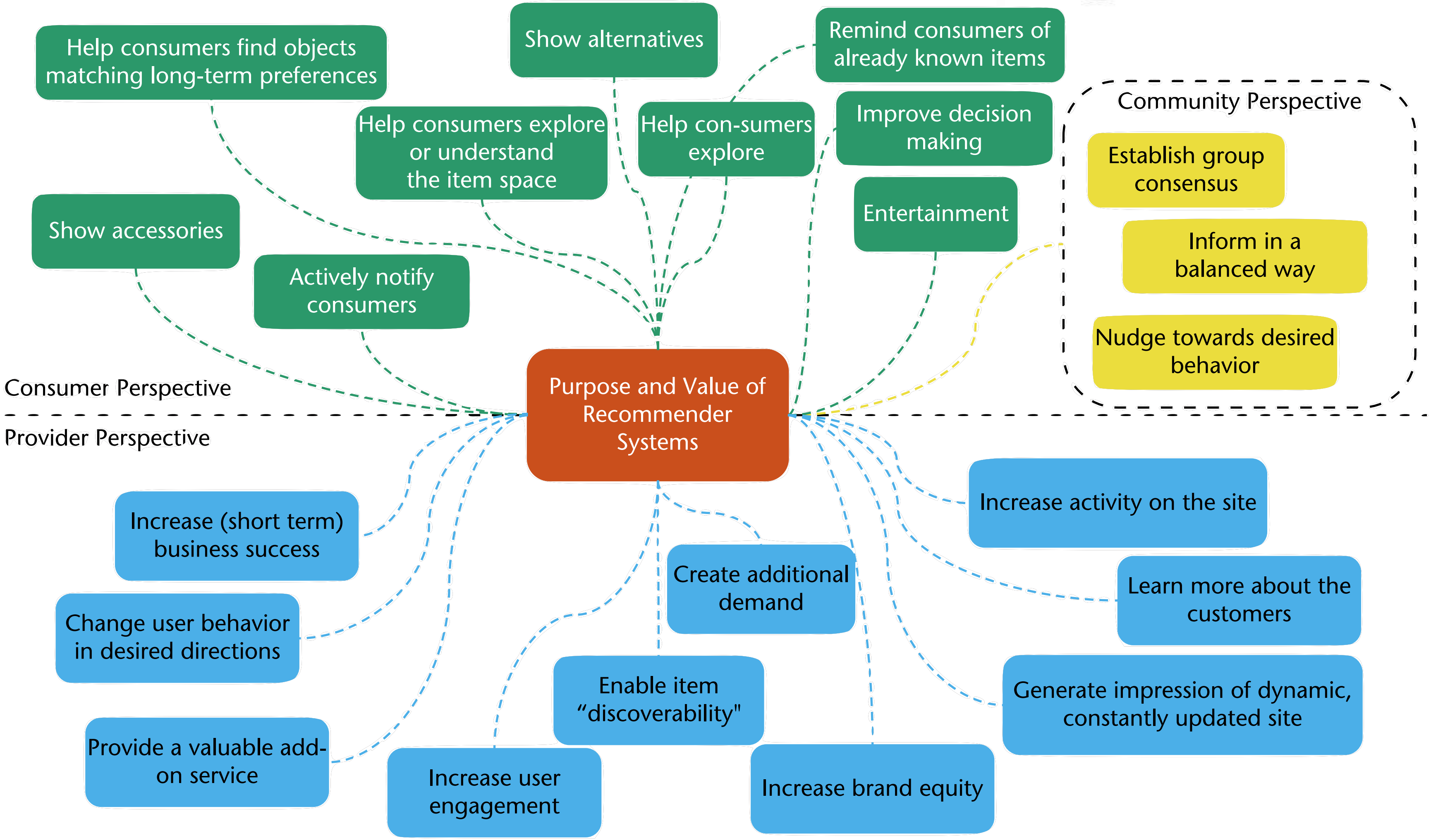
- What is my target group?
- Who else is affected/involved?
- Also consider sub-groups!

⚠⚠
In RecSys, mostly only the user is considered as a stakeholder.
→ improve for user satisfaction
⚠⚠



Dietmar Jannach & Christine Bauer (2020). Escaping the McNamara Fallacy: Toward More Impactful Recommender Systems Research. AI Magazine, 41(4), pp 79-95. DOI: 10.1609/aimag.v41i4.5312

Purpose and value of recommenders

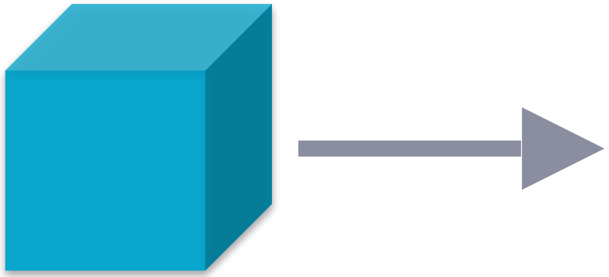


Dietmar Jannach & Gediminas Adomavicius (2016). Recommendations with a Purpose. In Proceedings of the 10th ACM Conference on Recommender Systems, RecSys 2016, 7–10. New York: ACM. DOI: 10.1145/2959100.2959186

Recommender systems paradigms

There are various ideas behind recommender systems—Paradigms of recommender systems

Whatever paradigm, recommender systems have in common that they **reduce information overload by estimating relevance**.



Recommendation component

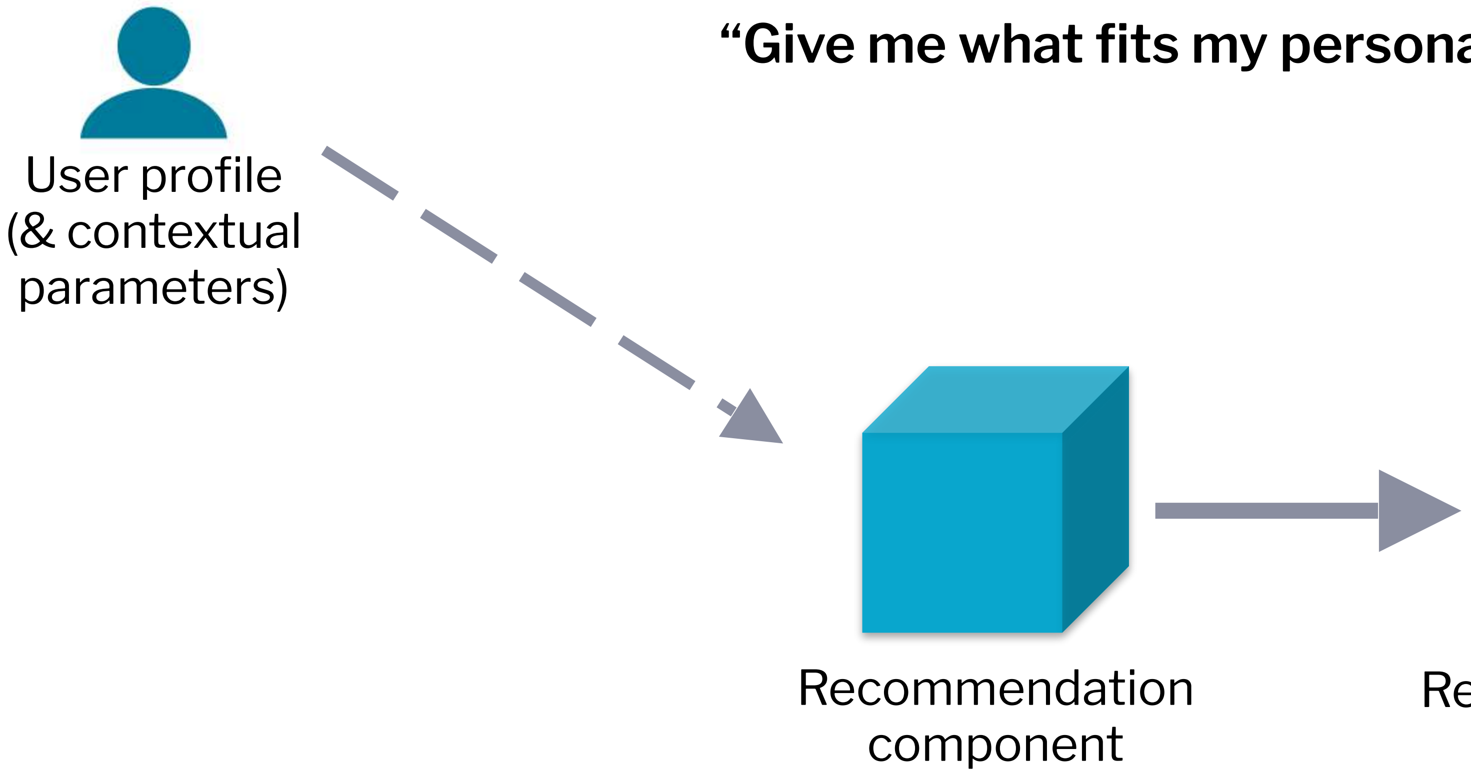
item	score
i1	0.9
i2	1.0
i3	0.3
…	…

Recommendation list

Dietmar Jannach, Markus Zanker, Alexander Felfernig, & Gerhard Friedrich (2011). Recommender systems: an introduction. Cambridge University Press.

Personalized recommendations

"Give me what fits my personal preferences"



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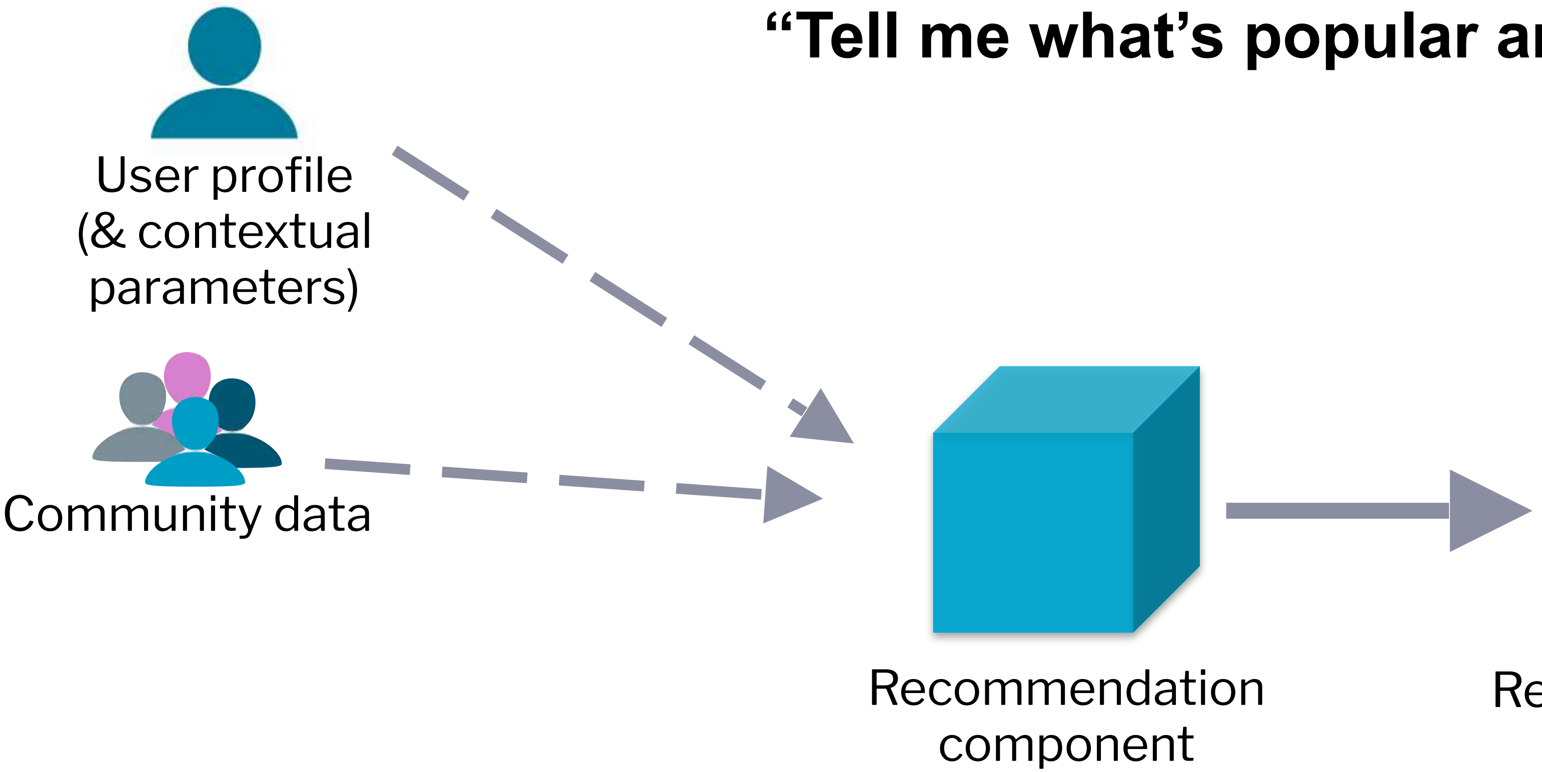
Recommendation list

Dietmar Jannach, Markus Zanker, Alexander Felfernig, & Gerhard Friedrich (2011). Recommender systems: an introduction. Cambridge University Press.

Collaborative

"Tell me what's popular among my peers"



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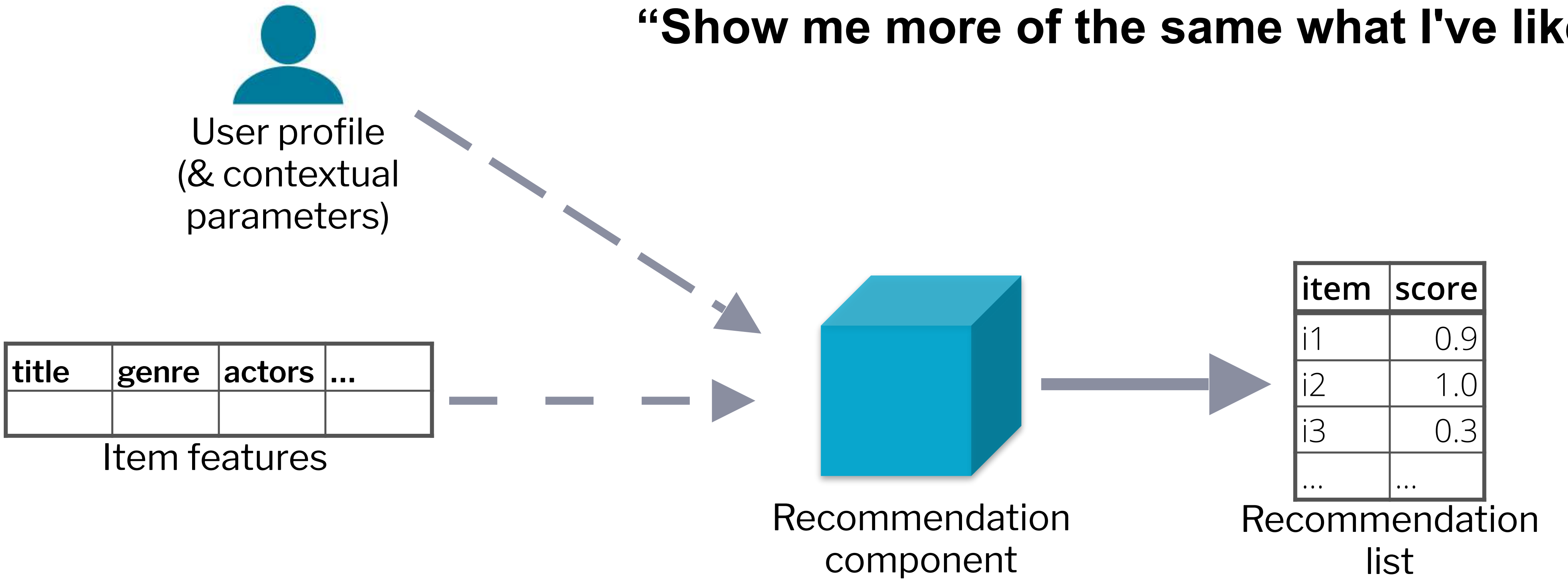
…	…

Recommendation list

Dietmar Jannach, Markus Zanker, Alexander Felfernig, & Gerhard Friedrich (2011). Recommender systems: an introduction. Cambridge University Press.

Content-based

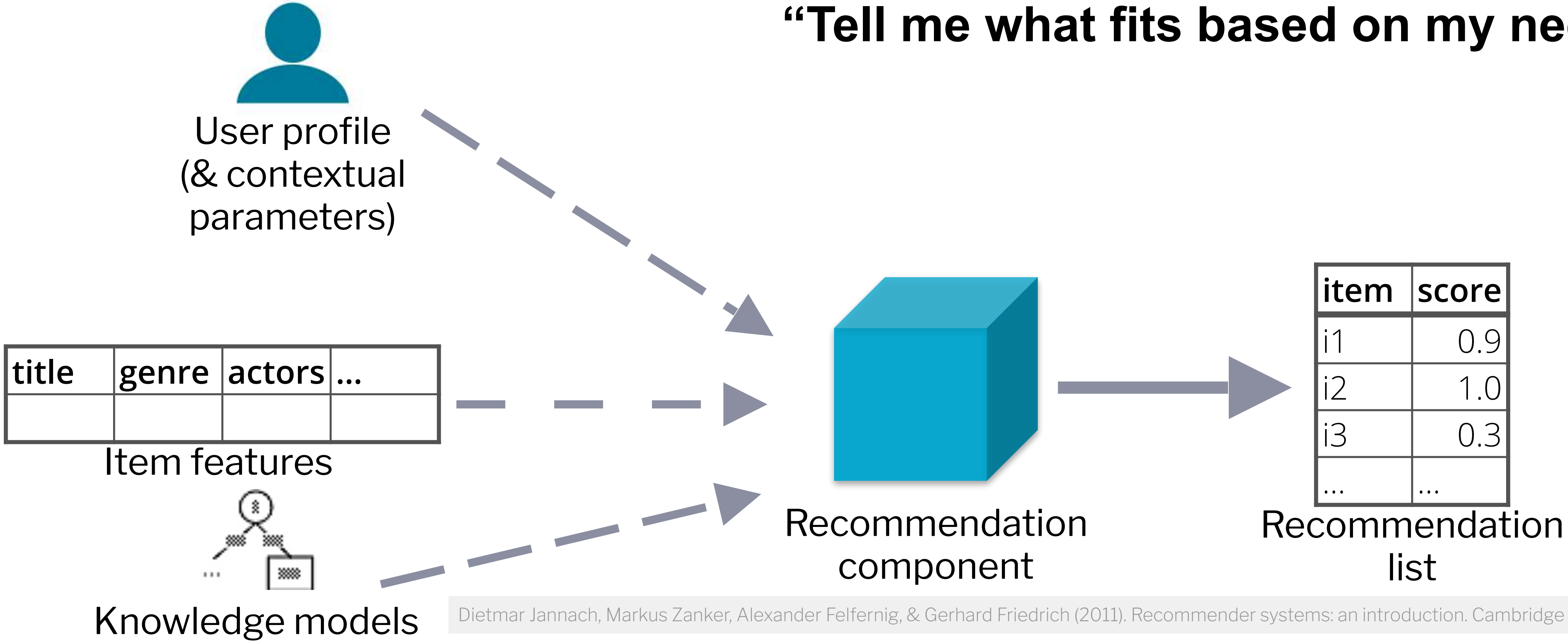
"Show me more of the same what I've liked"



Dietmar Jannach, Markus Zanker, Alexander Felfernig, & Gerhard Friedrich (2011). Recommender systems: an introduction. Cambridge University Press.

Knowledge-based

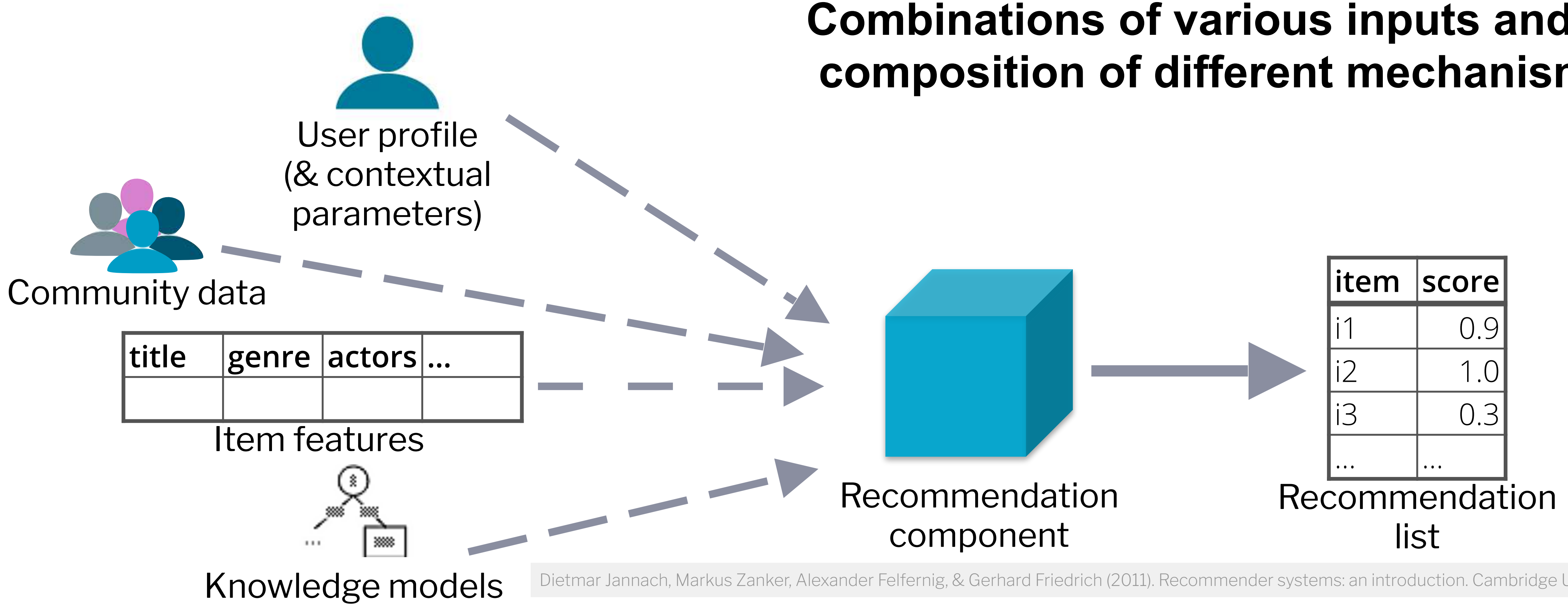
“Tell me what fits based on my needs”



Dietmar Jannach, Markus Zanker, Alexander Felfernig, & Gerhard Friedrich (2011). Recommender systems: an introduction. Cambridge University Press.

Hybrid

Combinations of various inputs and/or composition of different mechanisms



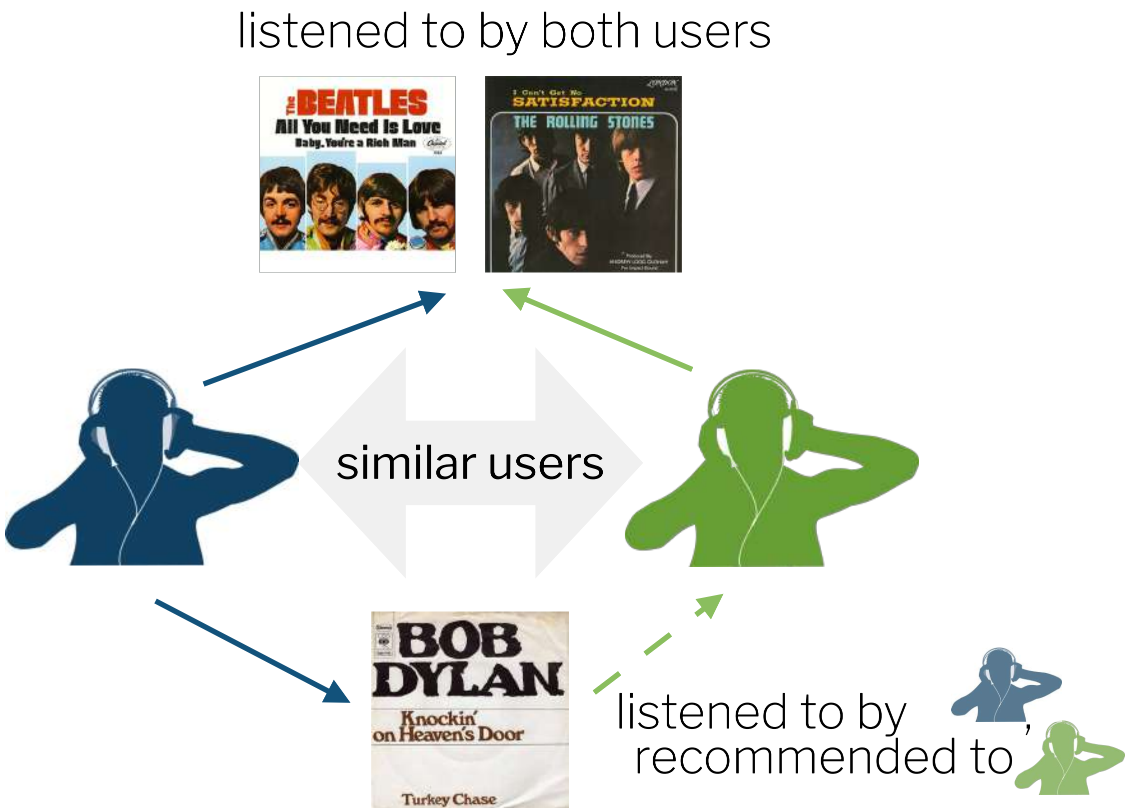
Dietmar Jannach, Markus Zanker, Alexander Felfernig, & Gerhard Friedrich (2011). Recommender systems: an introduction. Cambridge University Press.

How do recommender systems work?

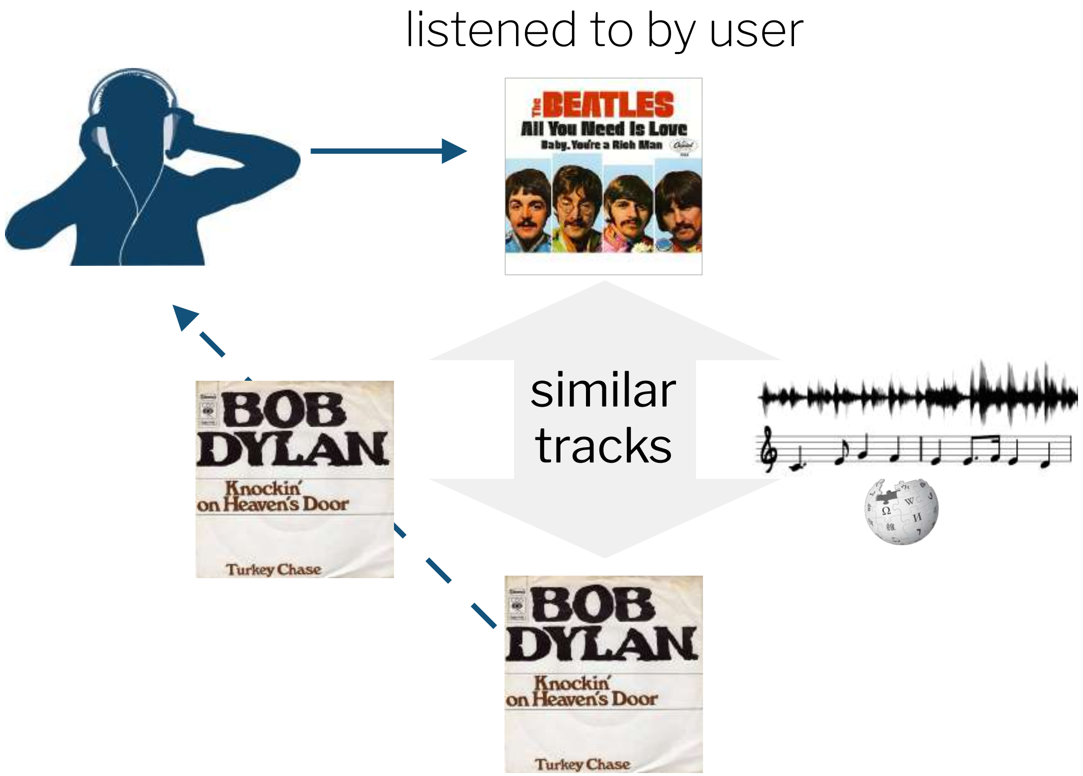
- Various filtering approaches exist.
- In essence, most go back to
  - **content-based filtering** and
  - **collaborative filtering**,
  - or combine these (**hybrid systems**).

Two basic approaches for filtering

Collaborative Filtering

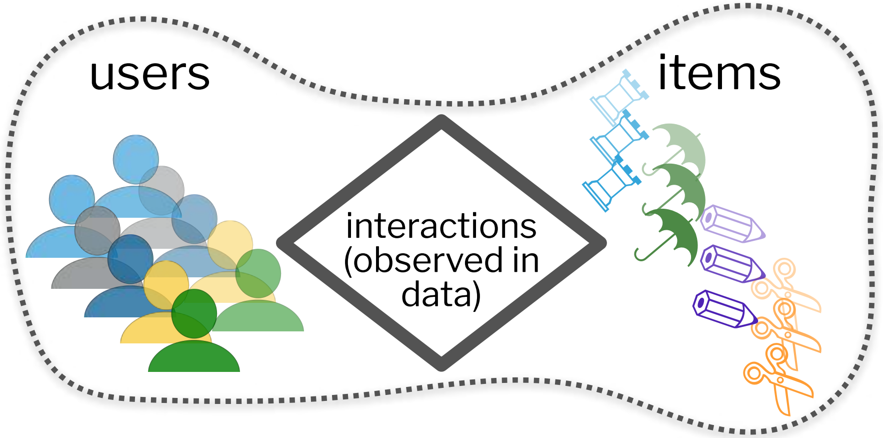


Content-based Filtering



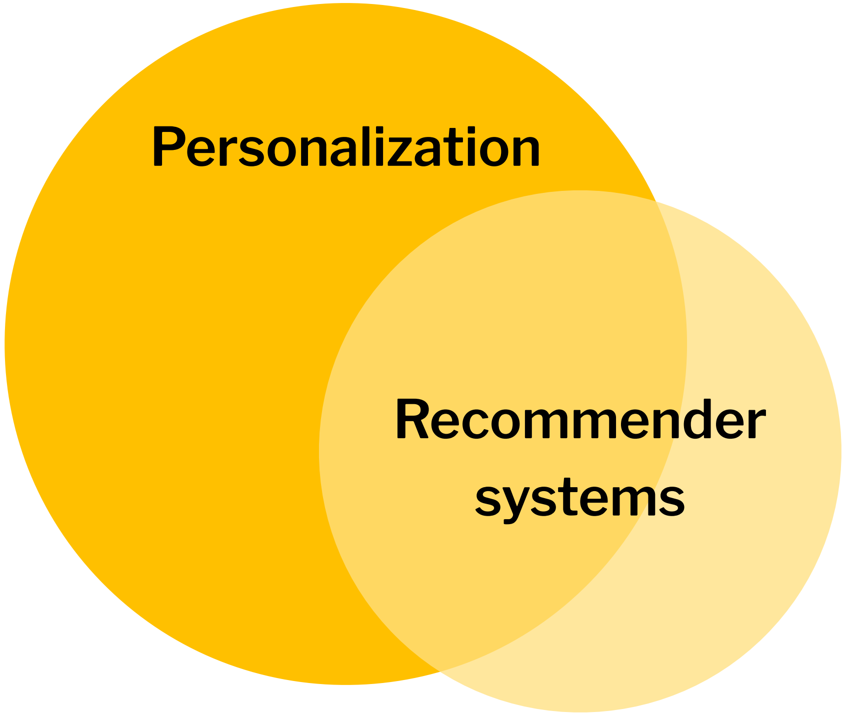
Delving deeper: Factors hidden in the data

- Observed data is the interaction of two factors: **users** and **items**

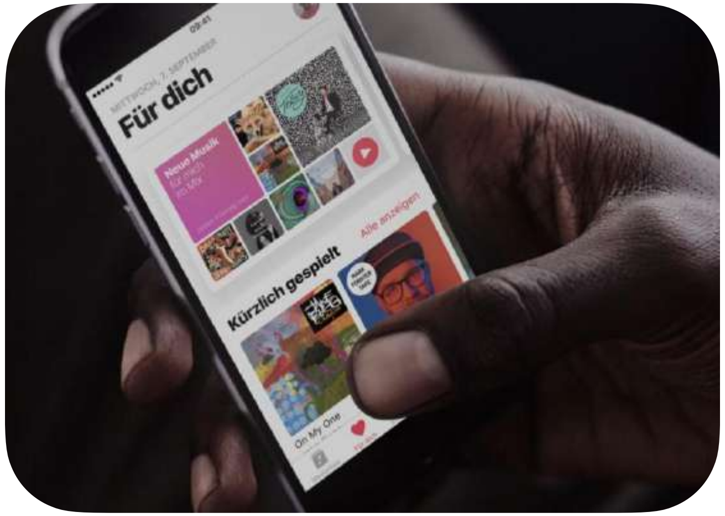


- **Consider users and items on a more fine-grained level**
  - Item descriptors: e.g., topic, genre, artist, tempo, danceability
  - User descriptors: e.g., gender, age, country, level of activity on platform

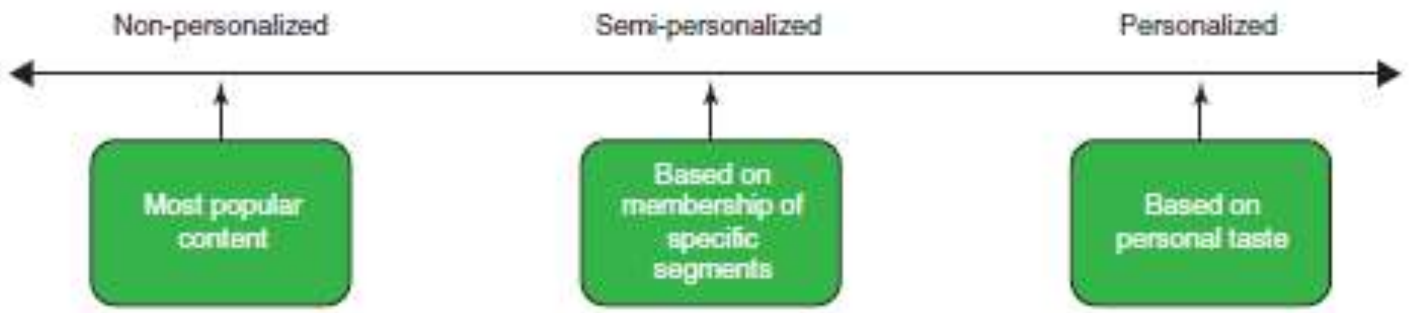
Context of recommender systems



Recommender help find items we like— for each person individually.



Levels of personalization



Kim Falk (2019), Practical Recommender Systems, Manning Publications, 2019, page 41.

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Content

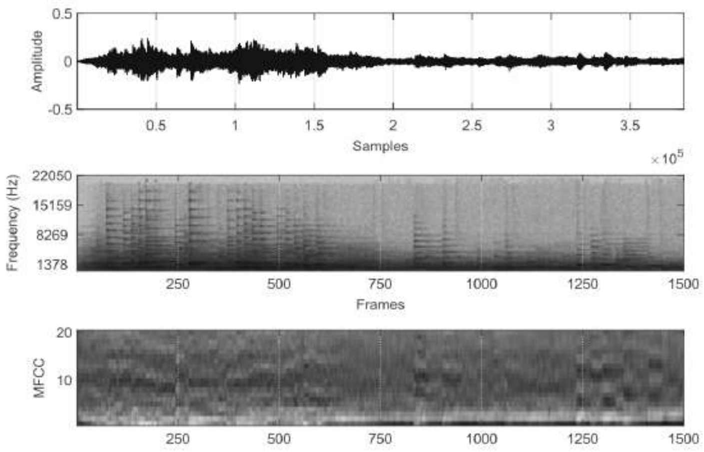
Which data describes music?

Audio content analysis

- In contrast to, e.g., movies: true content-based recommendation!
- Features can be extracted from any audio file
  → no other data or community data necessary
  → no cultural biases (no popularity bias, no subjective ratings, etc)
- Learning of high-level semantic descriptors from low-level features via machine learning
- → also human labeling plays a role

Audio content analysis: Selected features

- Human labelling
- Machine listening, content analysis

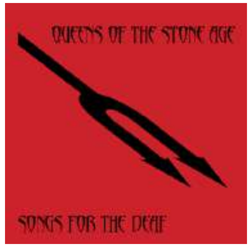


Musical descriptors	e.g., key, mode
Timbre	e.g. for genre classification, "more-like-this" recommendations
Beat/downbeat	e.g., time signature: 3/4, tempo: 85 bpm
Tonal features	e.g., for melody extraction, cover version identification
Semantic categories via machine learning	e.g., not_danceable, gender_male, mood_not_happy, instrumental
Features used by Spotify API	e.g., acousticness, danceability, energy, instrumentalness, liveness, loudness, speechiness, valence

Example
Audio Content Analysis: Selected Features

Disturbed
The Sound of Silence

- Timbre
  → e.g., for genre classification, “more-like-this” recommendations



- Beat/downbeat → Tempo: 85 bpm
- Tonal features
  → e.g., for melody extraction, cover version identification

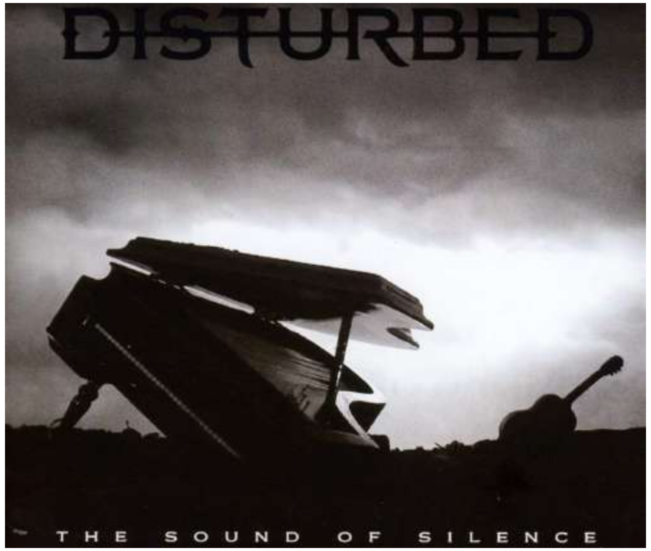

Different versions of this song, e.g.,
- Simon & Garfunkel—The Sound of Silence
- Anni-Frid Lyngstad (ABBA)—En ton av tystnad

- Semantic categories via machine learning
  → not_danceable, gender_male, mood_not_happy, ...

Schedl, Knees, Gouyon (2018). ISMIR Tutorial: Overview and New Challenges of Music Recommendation Research.

Audio is not the only available data about items

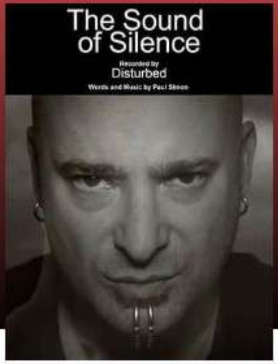
Artwork



Single cover

Album cover

Audio is not the only available data about items



The Sound of Silence

Disturbed

Track 11 on Immortalized ↴

Produced by
Kevin Churko

Release Date
August 21, 2015

View All Credits ↴

A cover of Simon & Garfunkel's 1964 song of the same name. Annotations that are not specific to this version can be found on the original. Style-wise, it differs greatly… Read More ↴

1 450.3K 70 45

The Sound of Silence Lyrics

[Verse 1]
Hello darkness, my old friend
I've come to talk with you again
Because a vision softly creeping
Left its seeds while I was sleeping
And the vision that was planted in my brain
Still remains within the sound of silence

[Verse 2]
In restless dreams, I walked alone
Narrow streets of cobblestone
'Neath the halo of a street lamp
I turned my collar to the cold and damp
When my eyes were stabbed by the flash of a neon light
That split the night and touched the sound of silence

Audio is not the only available data about items

Video

Music may be available…

- in symbolic format (e.g., a MIDI file)
- in audio format (e.g., an mp3 file)
- in vector format (e.g., a scanned score)

- in text format (e.g., lyrics as text)
- in vector format (e.g., album covers)
- in video format (e.g., music video)

Editorial and curatorial meta-data

e.g., genre, artist, release year

multi-modal

There is even more interesting data available.

- Editorial and curatorial meta-data
  - → e.g., genre, artist, release year
- User-generated data
  - → e.g., tags, reviews, stories, social media
- Curated collections
  - → Playlists, radio channels
  - → CD album compilations

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Recommender Systems 1

Day 2

Challenges

Data sparsity

Typically a large set of users and/or a large set of items
→ User-item matrix used for collaborative filtering could be extremely large and sparse

One typical problem caused by the data sparsity is
the **cold start problem**.

Cold Start Problem

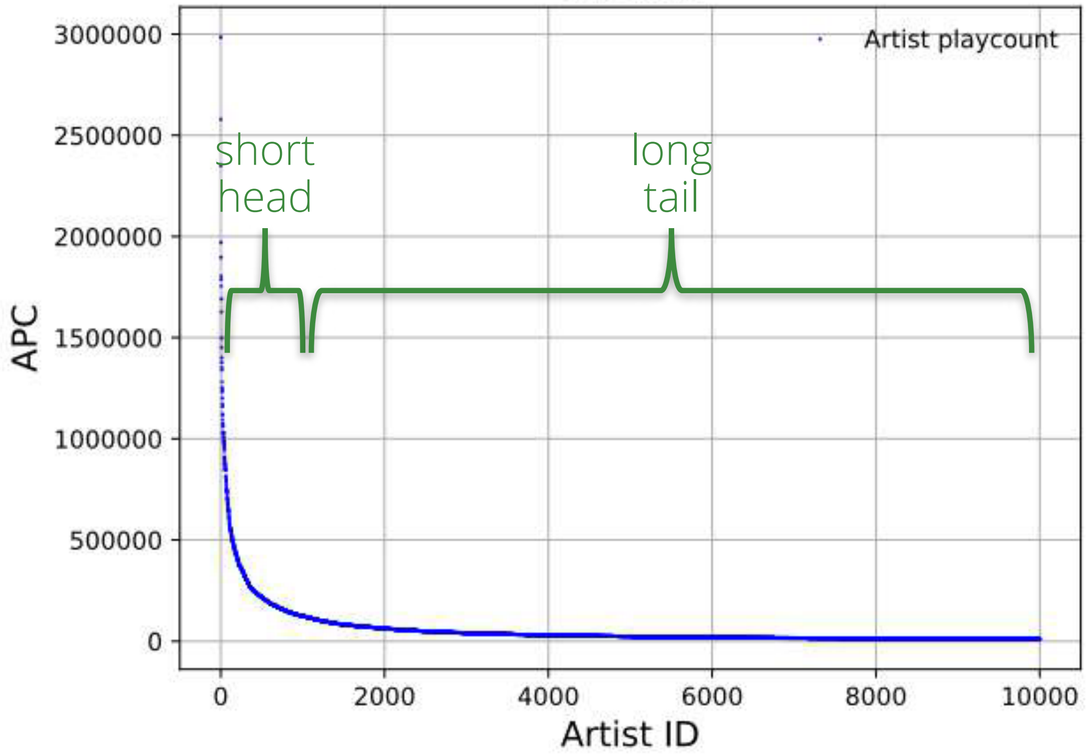
New user problem	New item problem
▪ **New user** enters the system → no historical data about preferences available (no user profile) ▪ Needs to rate sufficient number of items to enable the system to capture the personal preferences accurately and to provide reliable recommendations. ▪ Both for content-based and collaborative filtering (to different extent)	▪ **New items** are added to the system → do not appear in any user profile, no information about co-ratings ▪ Thus, new items need to be rated by a substantial number of users before they could be recommended to users who have similar tastes to the ones who rated them. ▪ The new item problem does not affect content-based recommendations, because item recommendations are based on its discrete set of descriptive qualities rather than its ratings.

Challenge of feature selection

- What does define “similarity” of items?
- Available content descriptors may not be sufficient
  - keywords alone may not be sufficient to judge quality/relevance of an item
    e.g., up-to-date-ness, usability, aesthetics, writing style (e.g., of web/text documents)
  - content may be limited / too short
  - content may not be automatically extractable (multimedia)

Popularity bias

- Typically, there is a long-tail distribution of popularity
- In collaborative filtering:
  - Items with more ratings are more likely to be recommended
  - Items with only a few ratings have less chance being recommended
- → Rich-get-richer effect for popular items



Artist playcount (APC) for the global top 10,000 artists. Artist IDs (x-axis) sorted by APC

Christine Bauer & Markus Schedl (2019). Global and country-specific mainstreaminess measures: Definitions, analysis, and usage for improving personalized music recommendation systems. PLOS ONE, 14(6), e0217389. DOI: 10.1371/journal.pone.0217389

Privacy-personalization paradox

- Effective personalization requires large amounts of user data
- With accurate, detailed, and up-to-date user profiles
  - → more reliable recommendations
  - Correlation between quality of user data and quality of recommendations
- Trade-off between personalization and data privacy (privacy-personalization paradox)
  - the more personal data is available → better recommendations are generated
  - the more personal data is available → less privacy users are remained with

Further challenges

Gray sheep	Overspecialization	Shilling attacks	Scalability

▪ Users whose opinions/ preferences do not consistently agree or disagree with any group of people
▪ → do not benefit from collaborative filtering
	▪ Content-based approaches tend to propose “more of the same”	▪ Gaming the system by actively rating items to one's own benefit
		  ▪ Positive ratings for one’s own items
		  ▪ Negative ratings for competitors
		▪ Collaborative filtering systems need to introduce precautions to discourage such kind of manipulations
			▪ With increasing numbers of users and items, traditional collaborative filtering will suffer serious scalability problems
			▪ Systems need to react immediately to online requirements and make recommendations for all users regardless of their feedback history

Challenges when working with explicit feedback

Data sparsity	Which items have (not) been rated?	Optimal granularity of scale	Multidimensional ratings
▪ No incentive to rate items: users are typically not willing to rate many items ▪ How to stimulate users to rate more items?	▪ Ratings are not missing at random; it has a structure	▪ Movie domain: 10-point scale tends to be accepted ▪ Music domain: uses thumbs up (down) ▪ Jokes recommender (e.g., Jester): uses a very fine-grained scale	▪ Multiple ratings per item (e.g., acting, directing, story plot,...)

Challenges when working with implicit feedback

- Correct interpretation of the (strength of the) action
  - e.g., buying something for a friend, accidental clicks
  - How to interpret shopping cart actions (recommend or not?)
- Huge amounts of data have to be processed

Changing User Interests (Dynamics)

- User model is often relatively static
- But dynamic evolution over user interests
  - Changes over time, older ratings may not be valid
  - Also called “interest/concept/profile drift”
- Also the context of recommendations
  - Example: Mobile restaurant guide
- Solutions in research literature include
  - Distinction between short- and long-term interests
  - Context-aware recommender systems