Recommender systems

RECOMMENDATION PROBLEM

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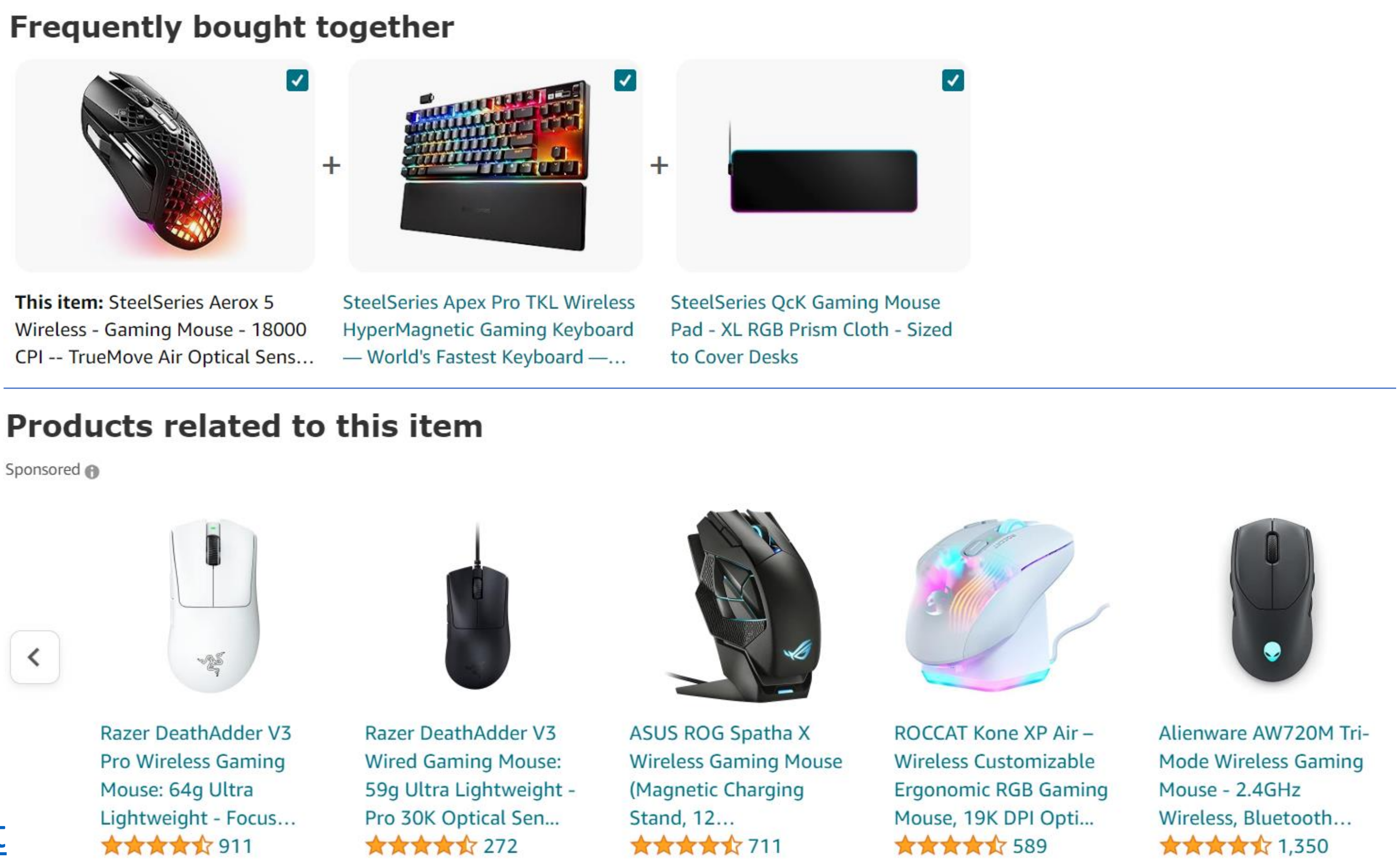
Content outline

- The recommendation problem
- Content-based recommendation
- Collaborative filtering

Recommender systems

- Recommender systems (RS) are widely used on the Web for suggesting products and services to users.



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Recommender systems

- RS are used in a wide variety of domains and industries.
- They help enhance user experiences, increase engagement, and improve business outcomes.

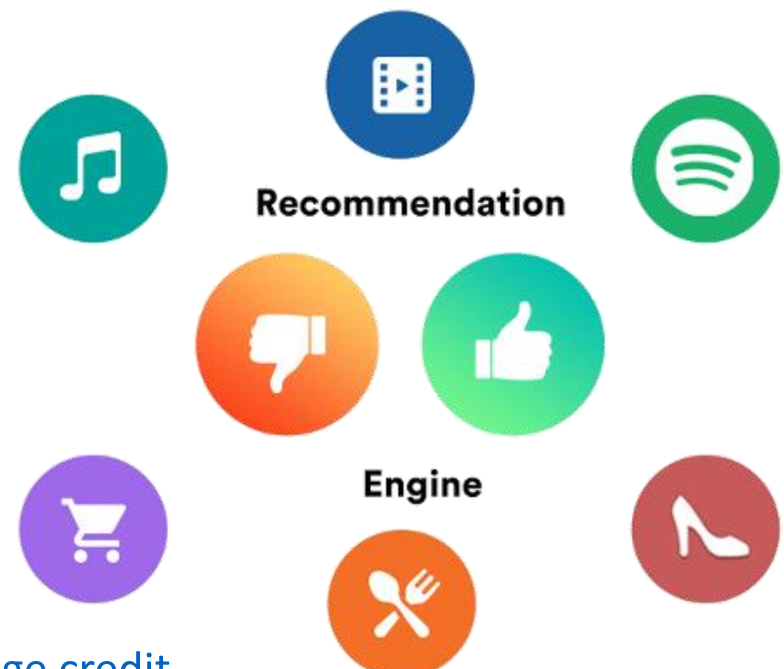


Image credit

Avengers: Endgame

2019 · PG-13 · 3h 1m

IMDb RATING
8.4/10
1.2M

YOUR

Action | Adventure | Drama

After the devastating events of Aveng
remaining allies, the Avengers assem
to the universe.

More like this

7.8

Captain America: Civil War

+ Watchlist

7.9

Thor: Ragnarok

+ Watchlist

8.4

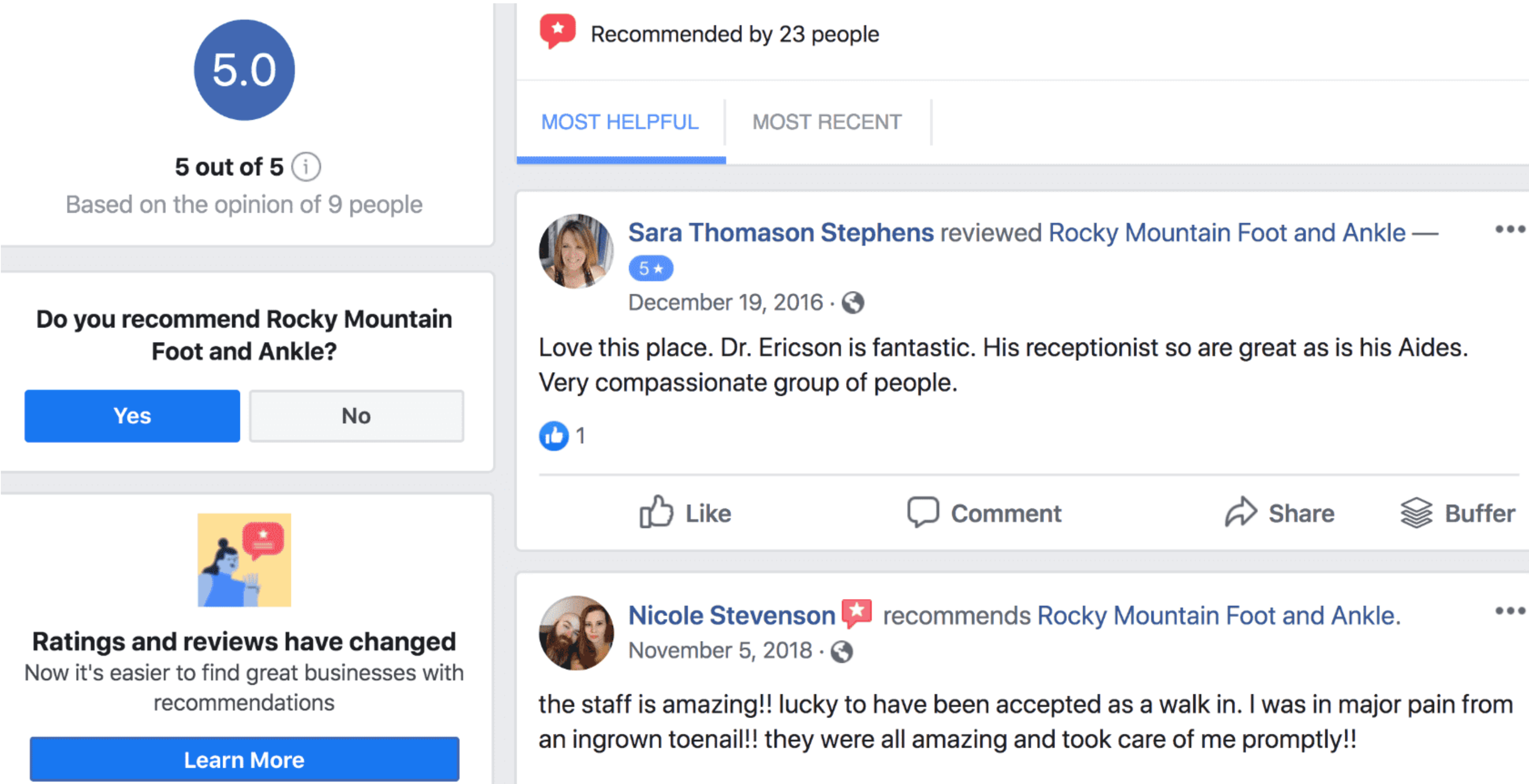
Joker

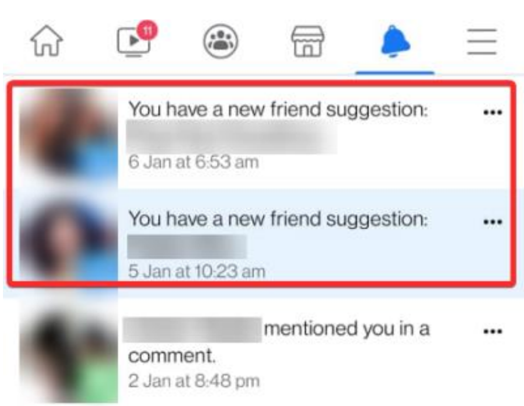
+ Watchlist

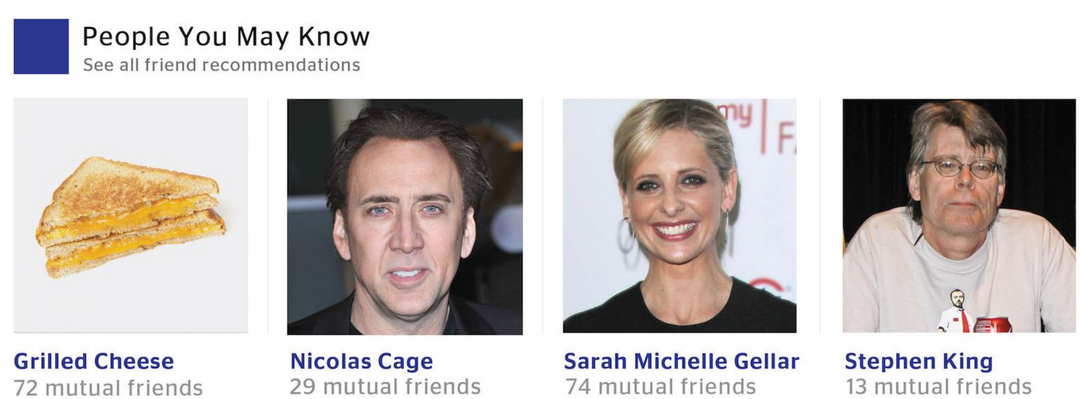
8.4

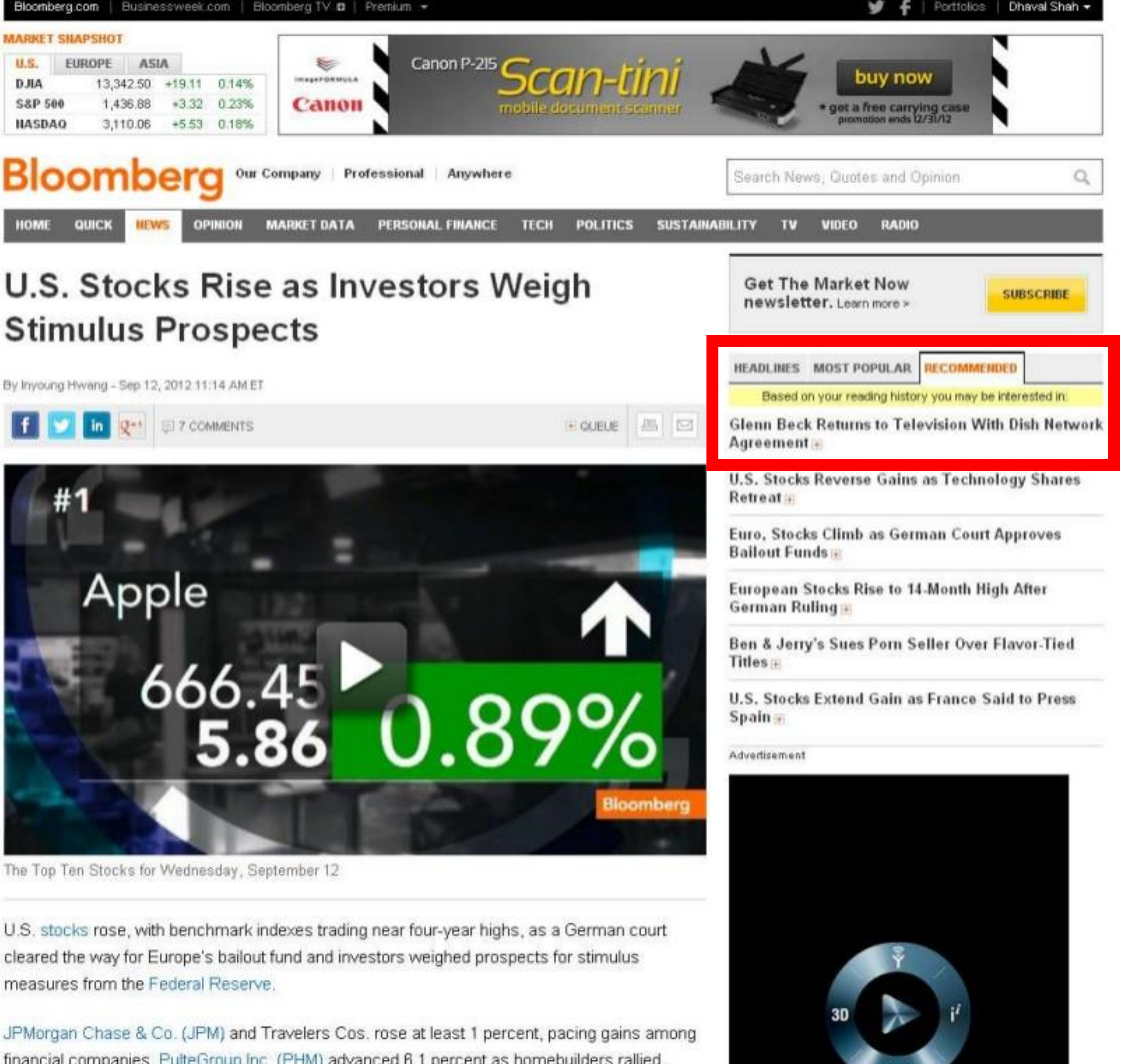
The Dark Knight Rises

+ Watchlist


5.0
5 out of 5
Based on the opinion of 9 people
Do you recommend Rocky Mountain Foot and Ankle?
Yes
No
Ratings and reviews have changed
Now it's easier to find great businesses with recommendations
Learn More
Recommended by 23 people
MOST HELPFUL
MOST RECENT
Sara Thomason Stephens reviewed Rocky Mountain Foot and Ankle — 5 ★
December 19, 2016 ·
Love this place. Dr. Ericson is fantastic. His receptionist so are great as is his Aides. Very compassionate group of people.
1
Like
Comment
Share
Buffer
Nicole Stevenson recommends Rocky Mountain Foot and Ankle.
November 5, 2018 ·
the staff is amazing!! lucky to have been accepted as a walk in. I was in major pain from an ingrown toenail!! they were all amazing and took care of me promptly!!


You have a new friend suggestion:
6 Jan at 6:53 am
You have a new friend suggestion:
5 Jan at 10:23 am
mentioned you in a comment.
2 Jan at 8:48 pm


People You May Know
See all friend recommendations
Grilled Cheese
72 mutual friends
Nicolas Cage
29 mutual friends
Sarah Michelle Gellar
74 mutual friends
Stephen King
13 mutual friends



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MARKET SNAPSHOT

U.S.	EUROPE	ASIA	
DJIA	13,342.50	+19.11	0.14%
S&P 500	1,436.88	+3.32	0.23%
NASDAQ	3,110.06	+5.53	0.18%

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U.S. Stocks Rise as Investors Weigh Stimulus Prospects

By Inyoung Hwang - Sep 12, 2012 11:14 AM ET

7 COMMENTS QUEUE

The Top Ten Stocks for Wednesday, September 12

U.S. stocks rose, with benchmark indexes trading near four-year highs, as a German court cleared the way for Europe's bailout fund and investors weighed prospects for stimulus measures from the Federal Reserve.

JPMorgan Chase & Co. (JPM) and Travelers Cos. rose at least 1 percent, pacing gains among financial companies. PulteGroup Inc. (PHM) advanced 6.1 percent as homebuilders rallied.

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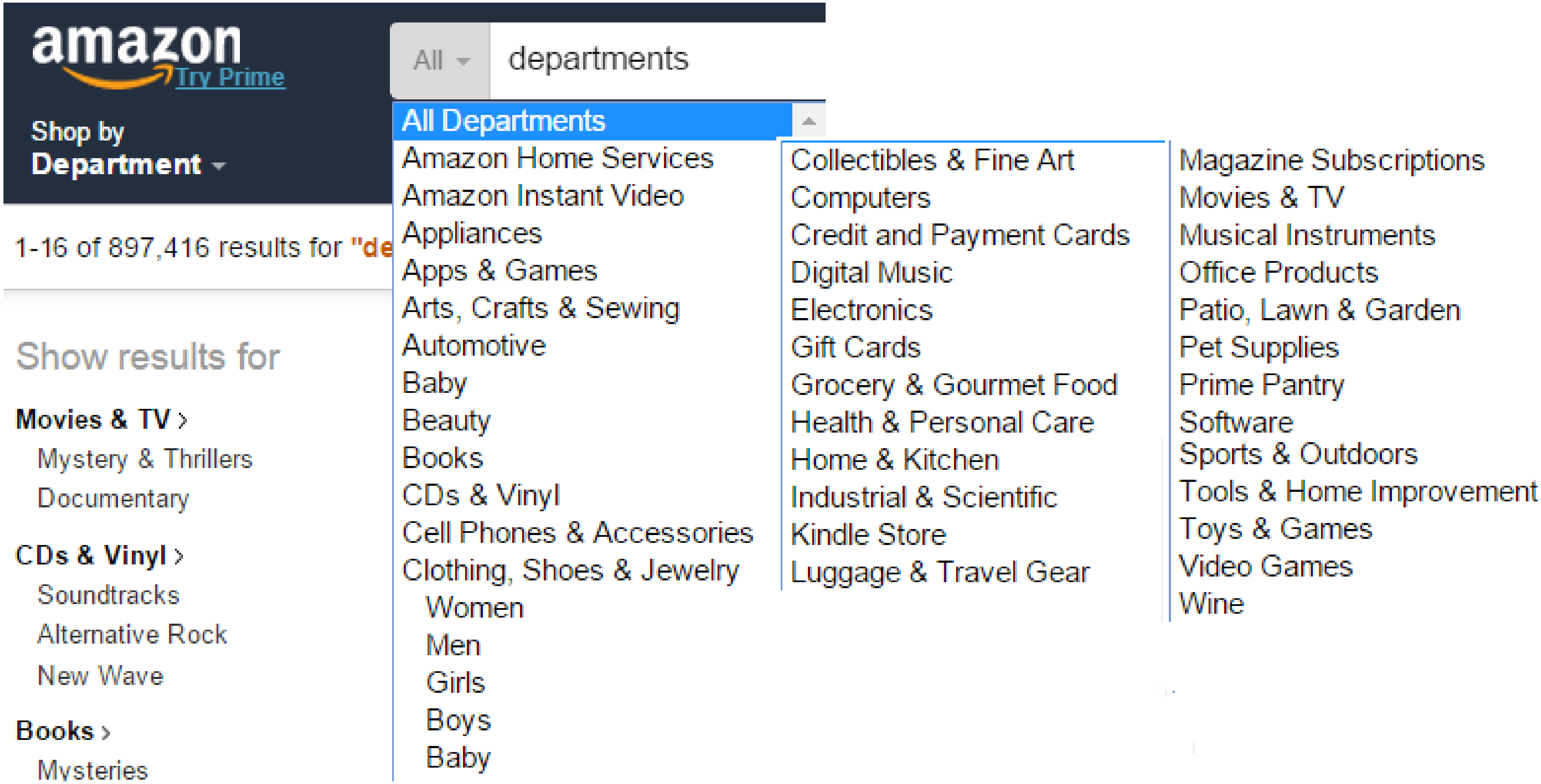
Building an AI-Powered Outfit Recommendation System With Dataiku
(2021)

Recommender systems

- These systems help users deal with the information overload by giving them personalized recommendations.
  - E.g., given thousands of movies, a RS selects and recommends some movies to each user that he will most likely enjoy watching.

Vast number of users and items

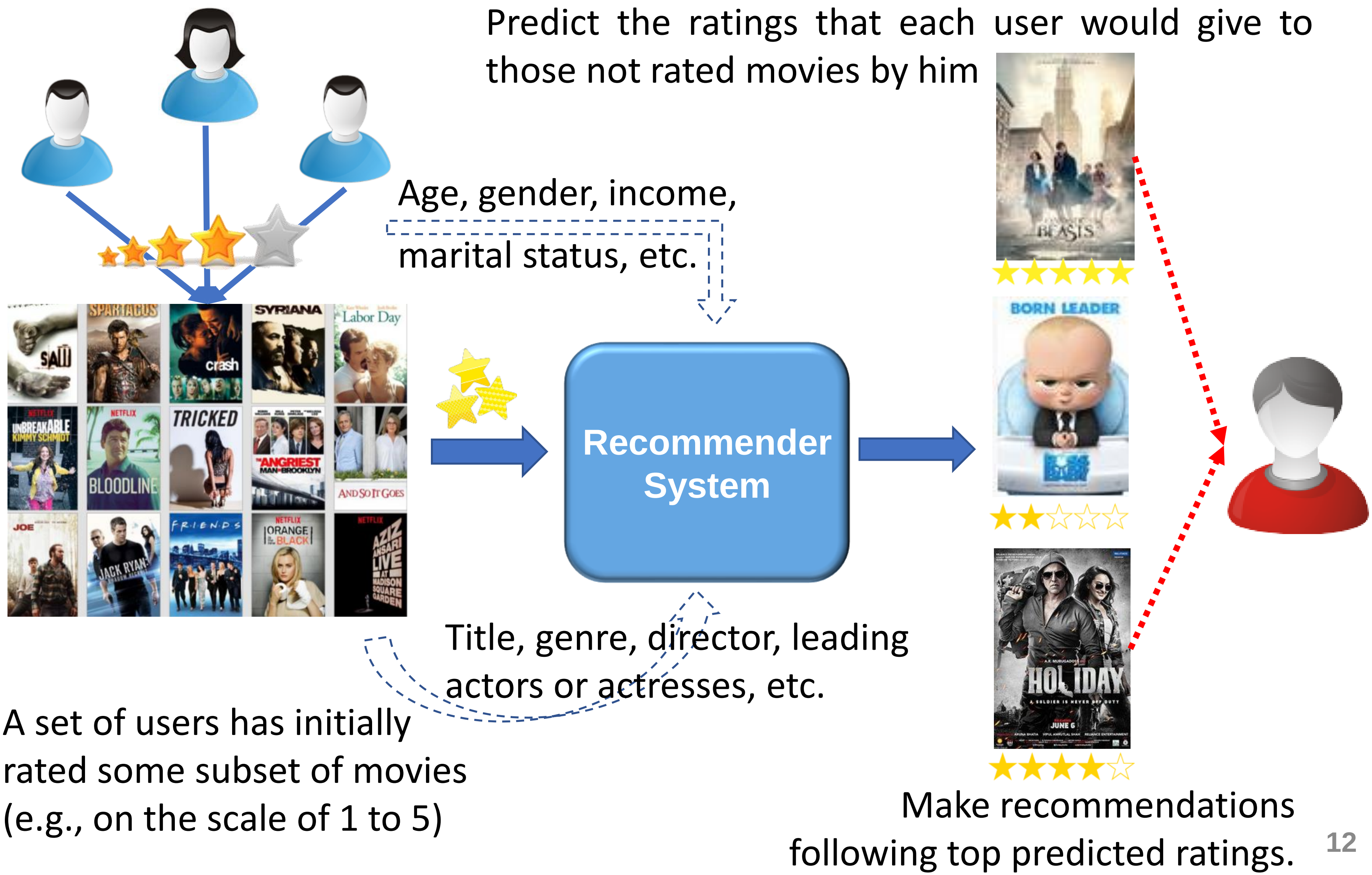


Amazon serves **350 million items** across 36 categories and other services. There are currently **150 million Prime subscribers** (2020).

Vast number of users and items

IMDb has roughly **7.5 million titles** (including episodes) and **10.4 million personalities**, and **83 million registered users**. (2020)

Movie recommendation

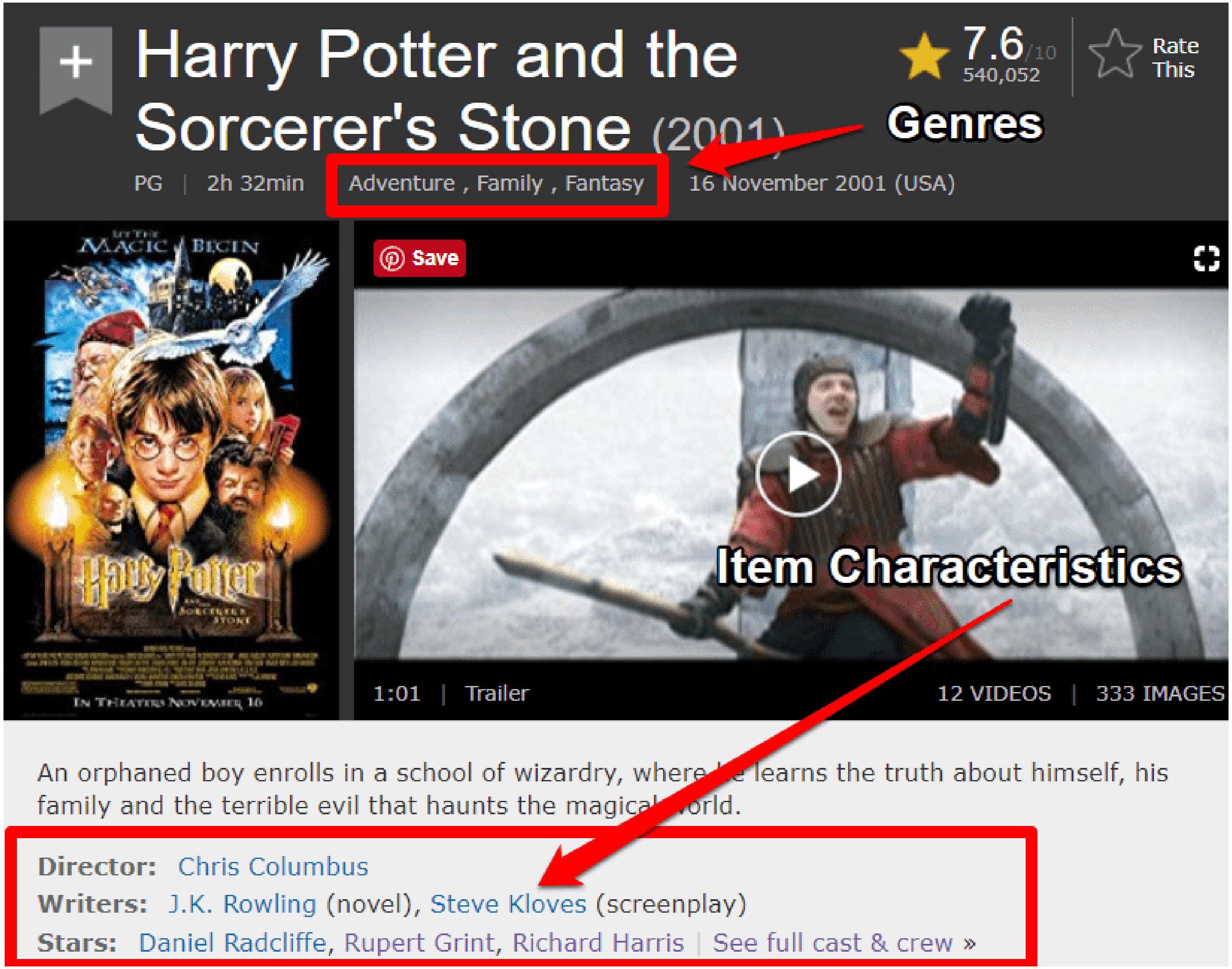


Recommendation problem

Users and items

- Let $\boldsymbol{U}$ be the set of users and $\boldsymbol{S}$ be the set of items to be recommended to the users.
- Each user $\boldsymbol{u} \in \boldsymbol{U}$ is defined with a user profile including various user characteristics.
    - E.g., UserID, age, gender, marital status, income, preferences, needs, usage behaviors, etc.
- Each item $\boldsymbol{s} \in \boldsymbol{S}$ is characterized by a set of features.
    - E.g., movie: FilmID, title, genre, director, year of release, actors, etc.
- In most applications, the spaces of $\boldsymbol{U}$ and $\boldsymbol{S}$ can be **huge**.

Users and items



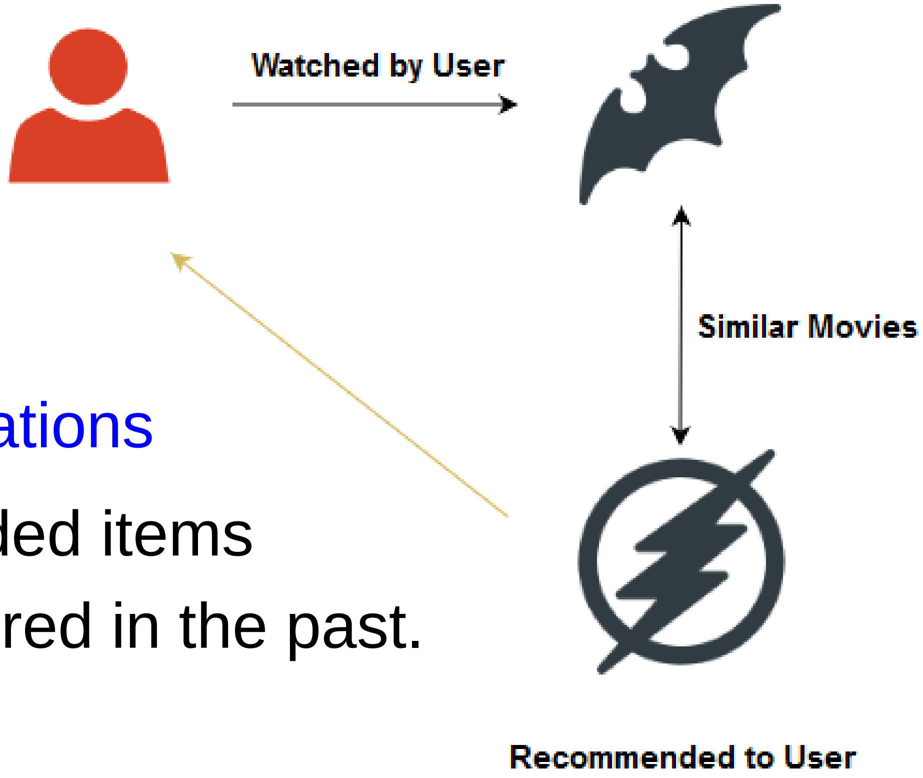
The recommendation problem

- Let $\boldsymbol{p} : \boldsymbol{U} \times \boldsymbol{S} \rightarrow \boldsymbol{R}$ be a utility function that measures the usefulness of item $\boldsymbol{s}$ to user $\boldsymbol{u}$.
  - $\boldsymbol{R}$ is a totally ordered set (e.g., non-negative integers or real numbers within a certain range).
- Learn the utility function $\boldsymbol{p}$
  - The objective function can be arbitrary and application-dependent, e.g., user satisfaction or seller profitability.
- Use $\boldsymbol{p}$ to predict the utility value of each item $\boldsymbol{s}$ ($\in \boldsymbol{S}$) to each user $\boldsymbol{u}$ ($\in \boldsymbol{U}$) and recommend the top-$\boldsymbol{k}$ items to user $\boldsymbol{u}$
  - Except items that already have utility values for $\boldsymbol{u}$ from the input data

The recommendation problem

- Rating prediction: forecast the rating score a user is likely to give to an item that he has not seen or used before
  - The utility of item s to user u is the rating given to item s by user u.
- Item prediction: conclude a ranked list of items that a user is likely to buy or use
  - The utility of item s to user u is typically expressed as the probability that user u will buy or use item s.
- User-item interactions are typically binary or multi-scaled (yet concrete values are unconcerned).

Approaches to recommendation

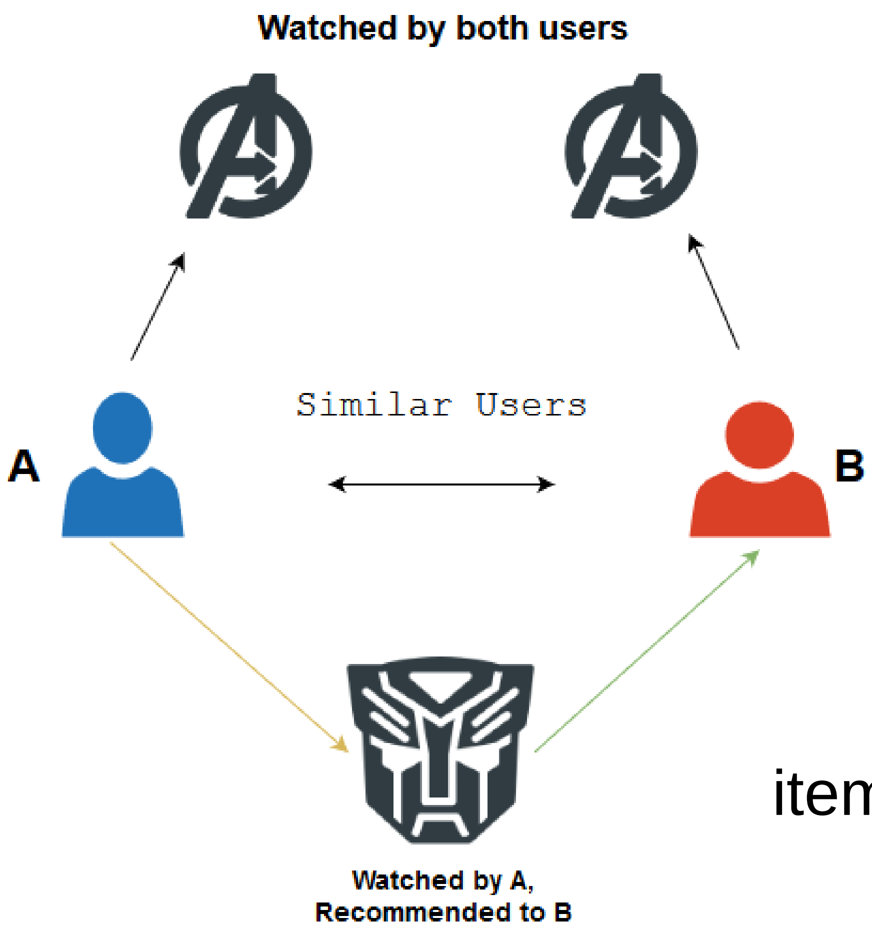


Content-based recommendations

The user will be recommended items similar to the ones he preferred in the past.

Image credit

Approaches to recommendation



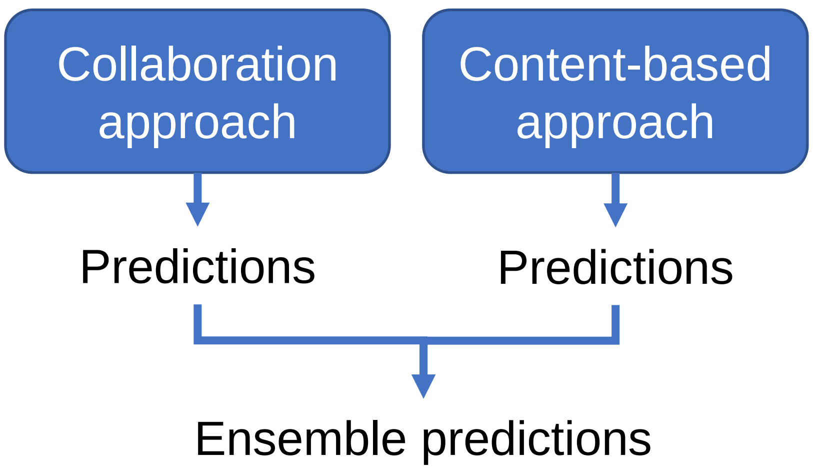
Collaborative filtering

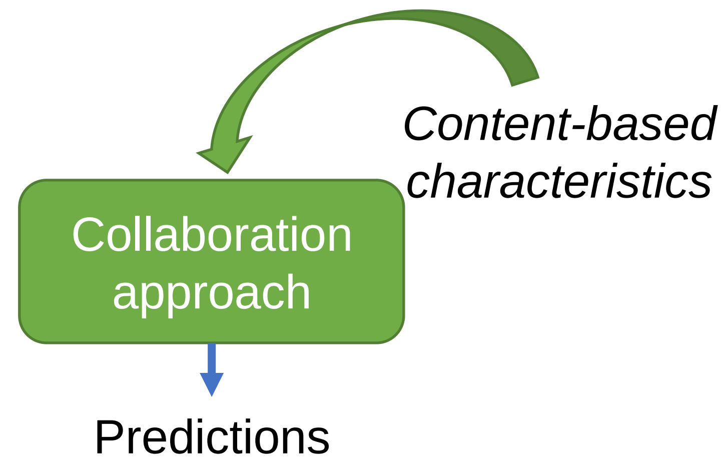
The user will be recommended items that people with similar tastes liked previously

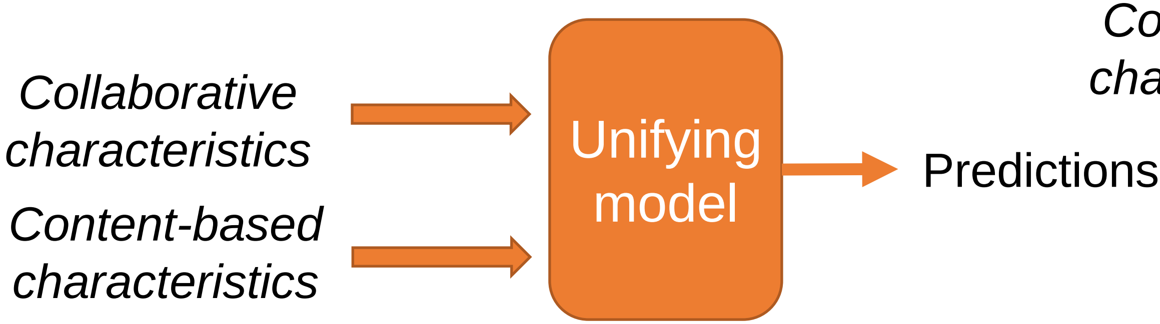
Image credit

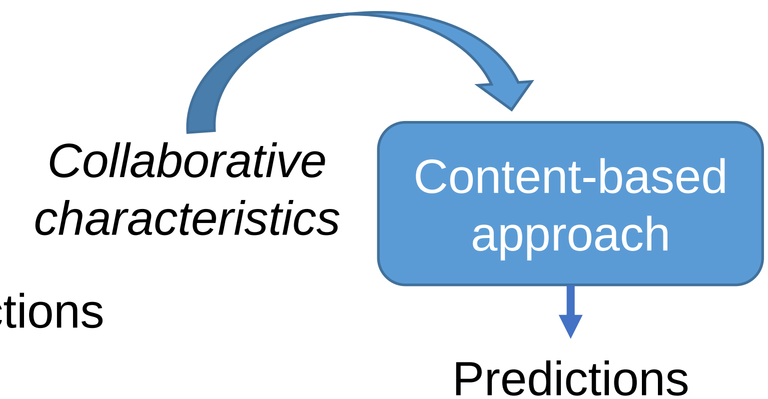
Hybrid approaches

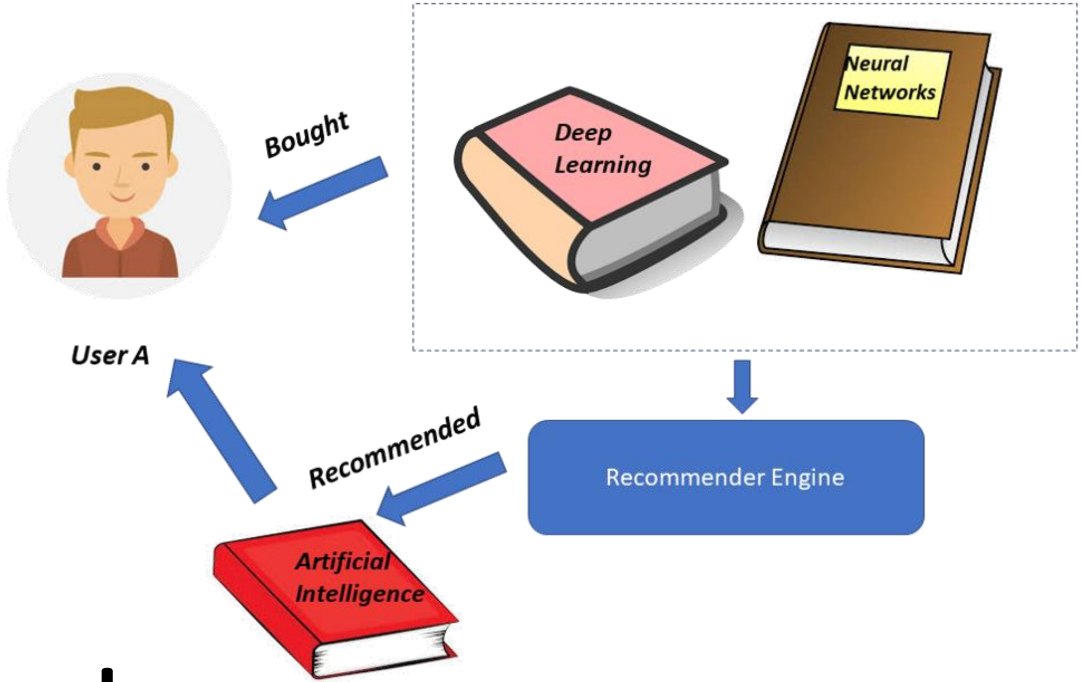
- Collaborative filtering and content-based recommendation can be combined in different ways.







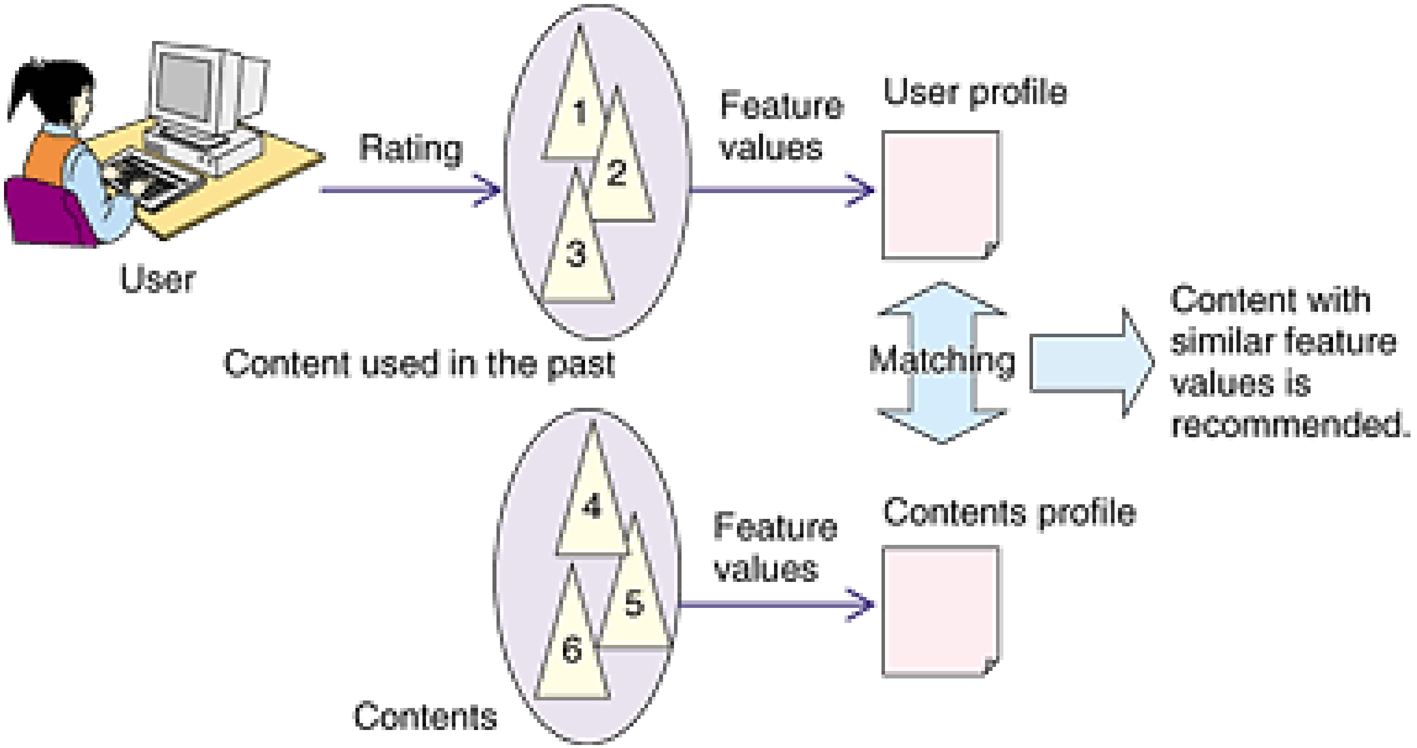




Content-based recommendation

Content-based recommendation

- Predict the utility of an item for a particular user based on how “similar” the item is to those that he liked in the past

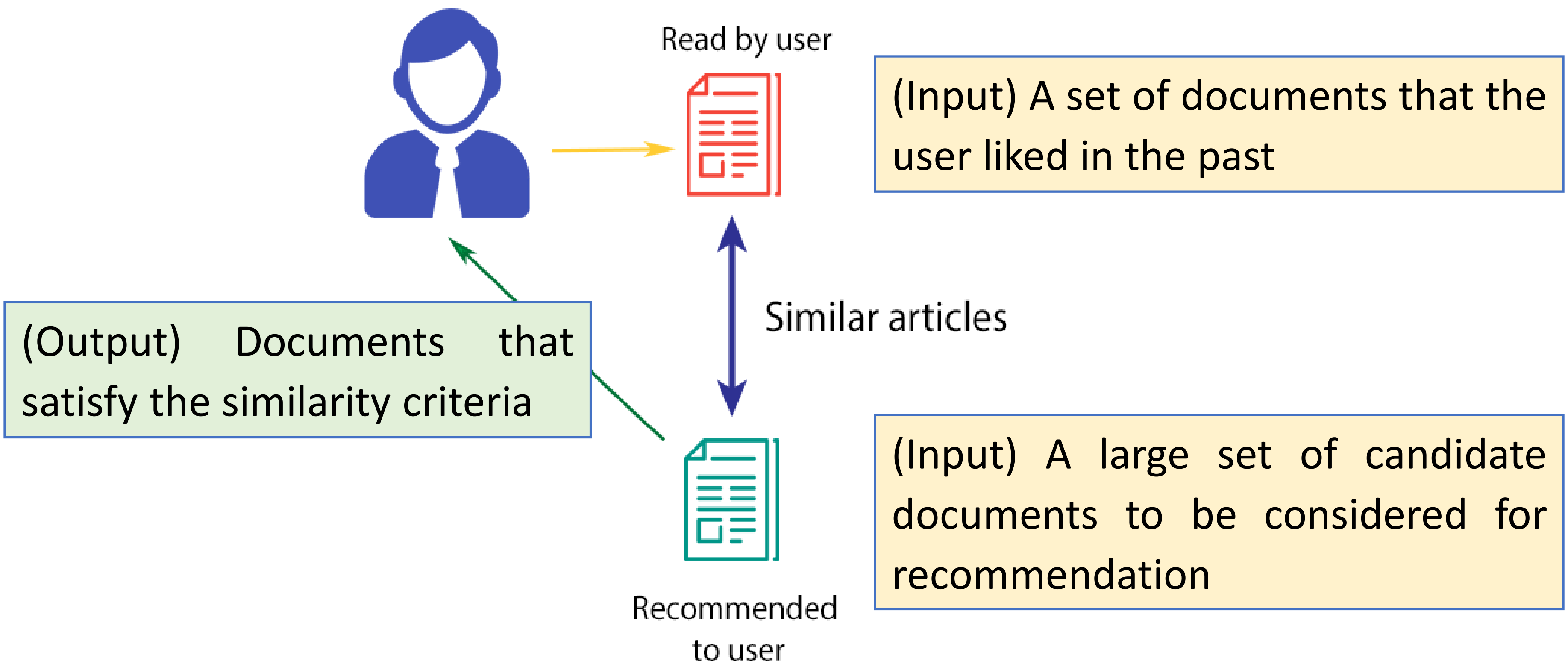


Users and items

- An item is usually represented by a set of features.
  - E.g., a movie – actors, director, genre, subject matter, etc.
- A user profile is also defined by the same set of features.
  - This profile can be **learnt explicitly** from the user (e.g., through questionnaires) or **implicitly** from his usage behavior over time.
- Top-k similar items are presented to the user after matching his profile and candidate items on the same set of features.

Text document recommendation

- Content-based recommendation is primarily applied to the domain of text documents.
  - E.g., recommend news articles, Web pages, and blogs

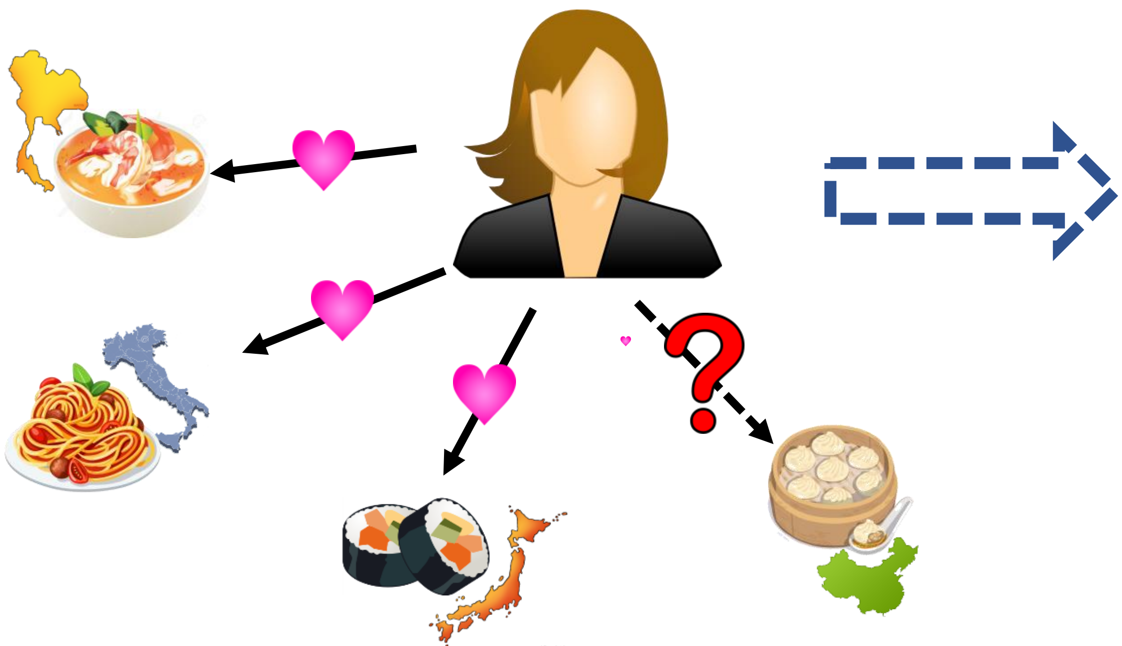


Text document recommendation

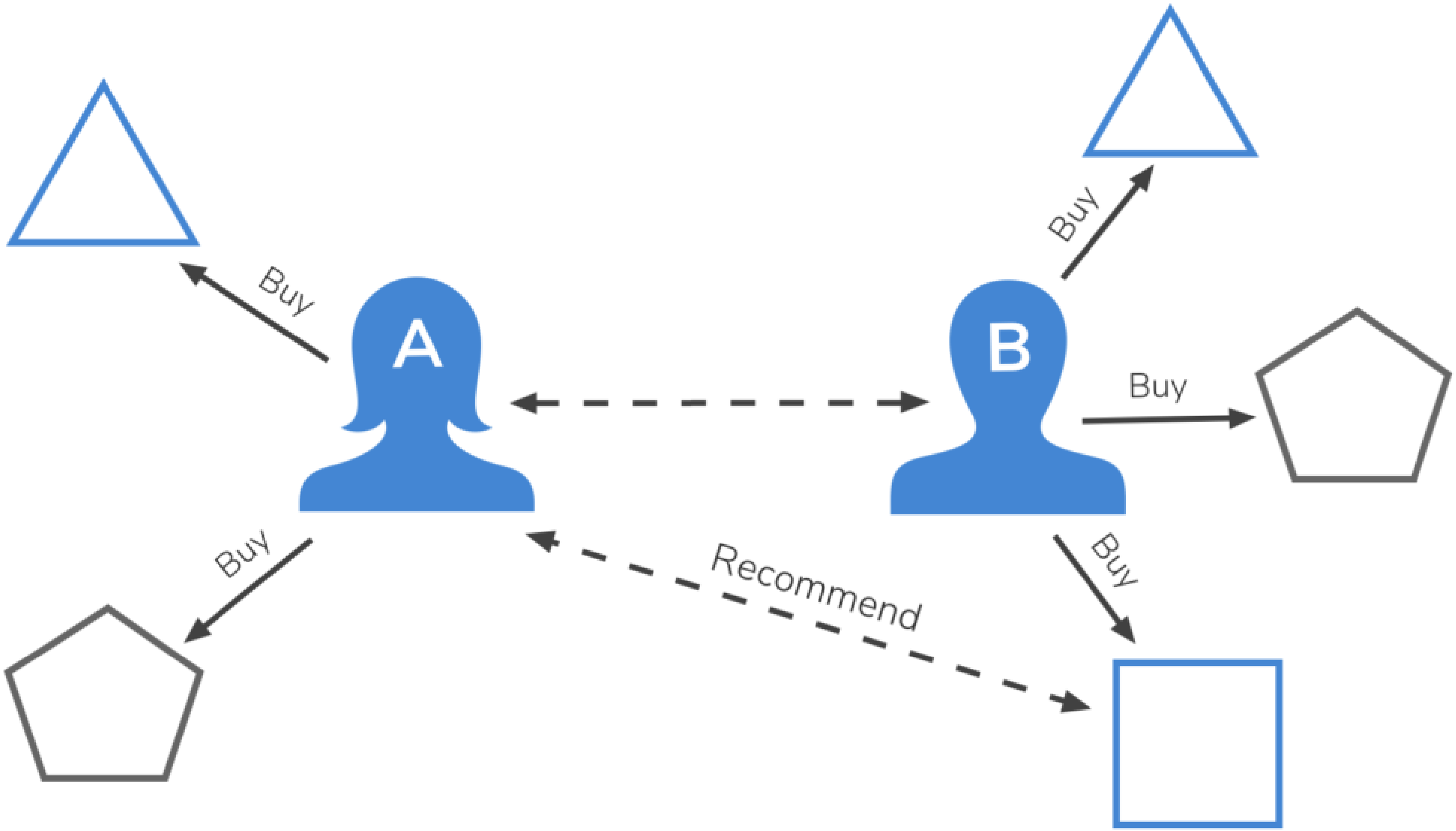
- Most techniques are based on those in information retrieval.
- We define each document by a feature vector and each user profile on the same set of features.
    - Document: a vector of keywords using the TF-IDF scheme in the vector space model
    - User profile: an “average” / “abstract” vector of relevant documents
- The system uses common similarity metrics to match the user profile with candidate documents.
    - E.g., Euclidean distance, cosine similarity, etc.

Limitations

- Items dissimilar to those the user liked in the past are not recommended by the system.
- The user will never see anything completely novel but could be of interest → the business gains less profit from the user.

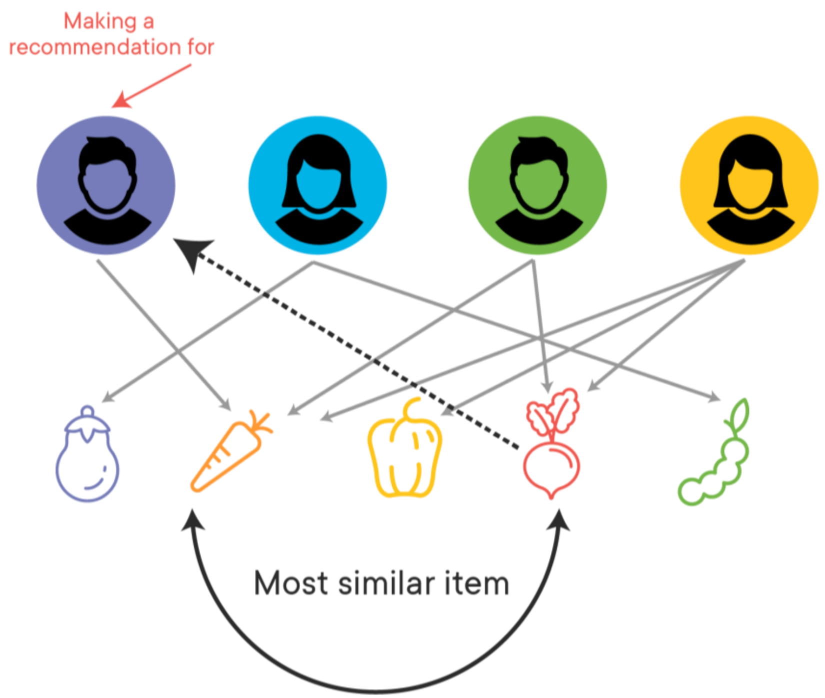


Collaborative Filtering

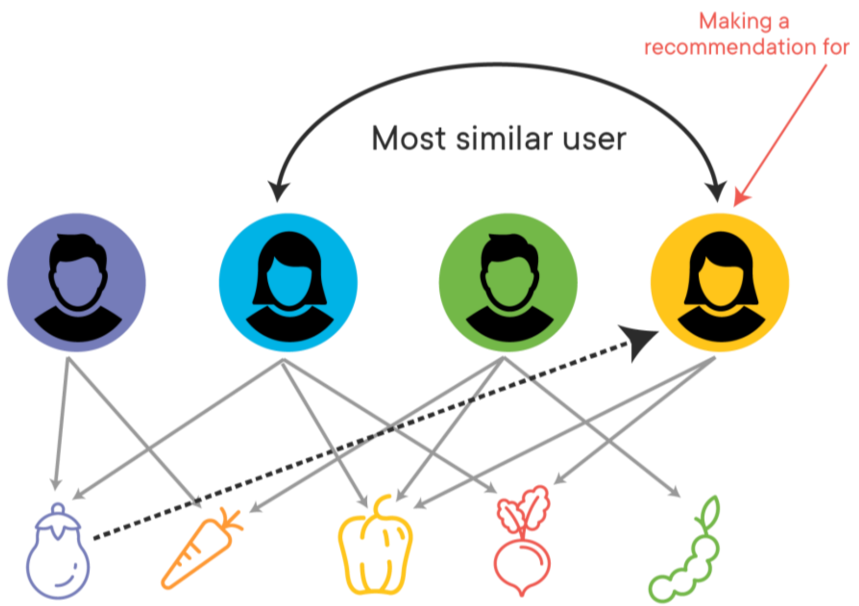


Collaborative filtering (CF)

- CF derives the utility of an item for a particular user from the items previously considered by other like-minded users.



Item-based collaborative filtering (IBCF)



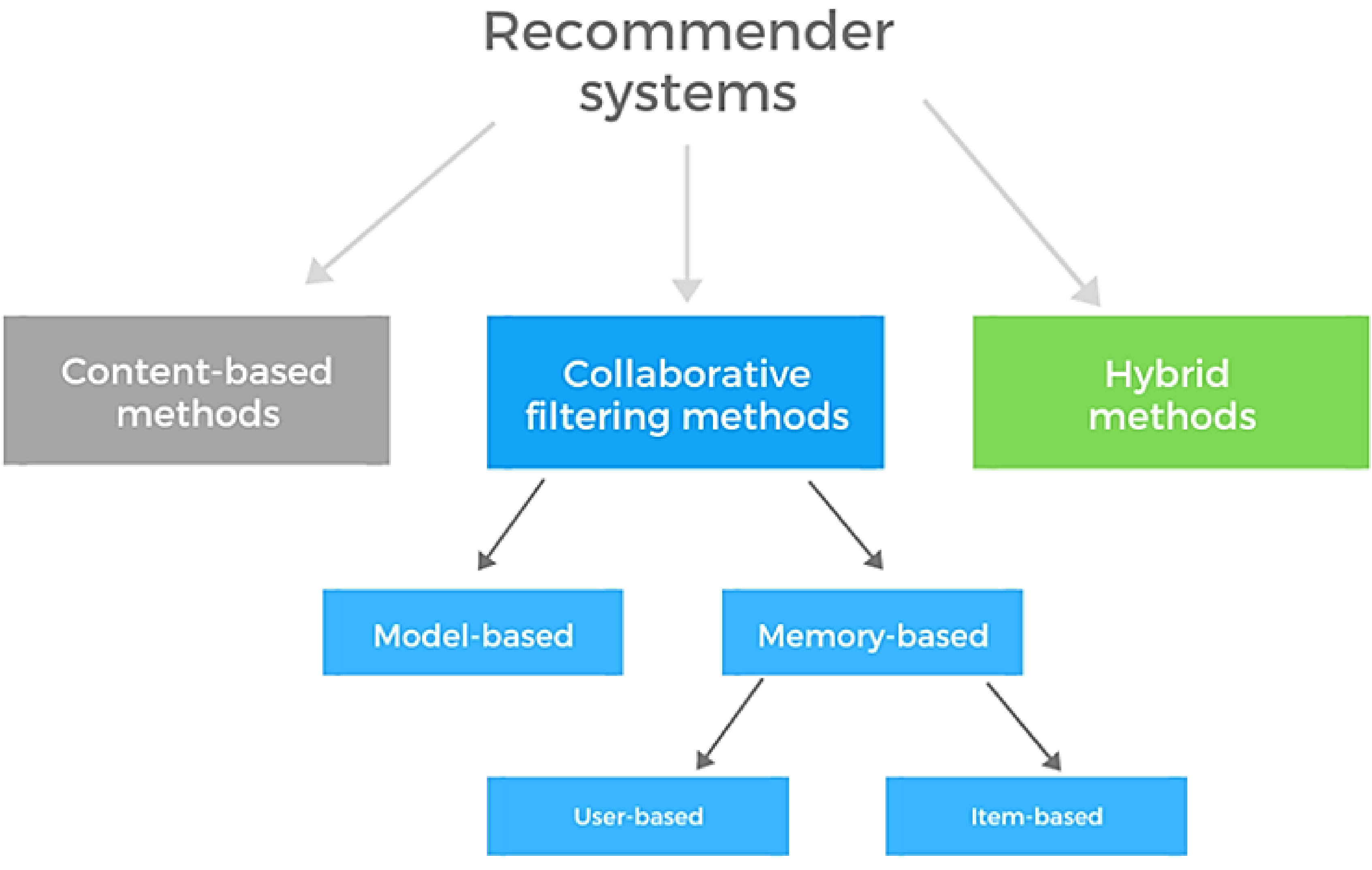
User-based collaborative filtering (UBCF)

Image credit

Collaborative filtering types

- A CF system often utilizes only the interaction between consumers and items while ignoring their attributes.
- User-based collaborative filtering (UBCF)
  - Find **users** that have similar tastes to that of the target user
  - Predict the item that the target user might like based on ratings given to that item by those “similar” users
- Item-based collaborative filtering (IBCF)
  - Find **items** that are “similar” to the candidate item, using the ratings given to each pair of items by users who have rated them both
  - Predict the likelihood that the target user might like the candidate item based on the ratings given to those “similar items” by him

Collaborative filtering types



Collaborative filtering types

Memory-based	Model-based
complete input data is required	abstraction (model) that represents input data
does not scale well	scales well
pre-computation not possible	pre-computation possible
relies on similarity metrics between users and items	relies on matrix factorization

Feedback types

- Most CF algorithms are based on certain statistical models of user interests built from user feedbacks.

Explicit feedbacks

- Preferences given by the user directly to the item, using one or more ordinal / qualitative scales.
  - E.g., users giving ratings to movies
- More precise but more difficult to collect from users

Implicit feedbacks

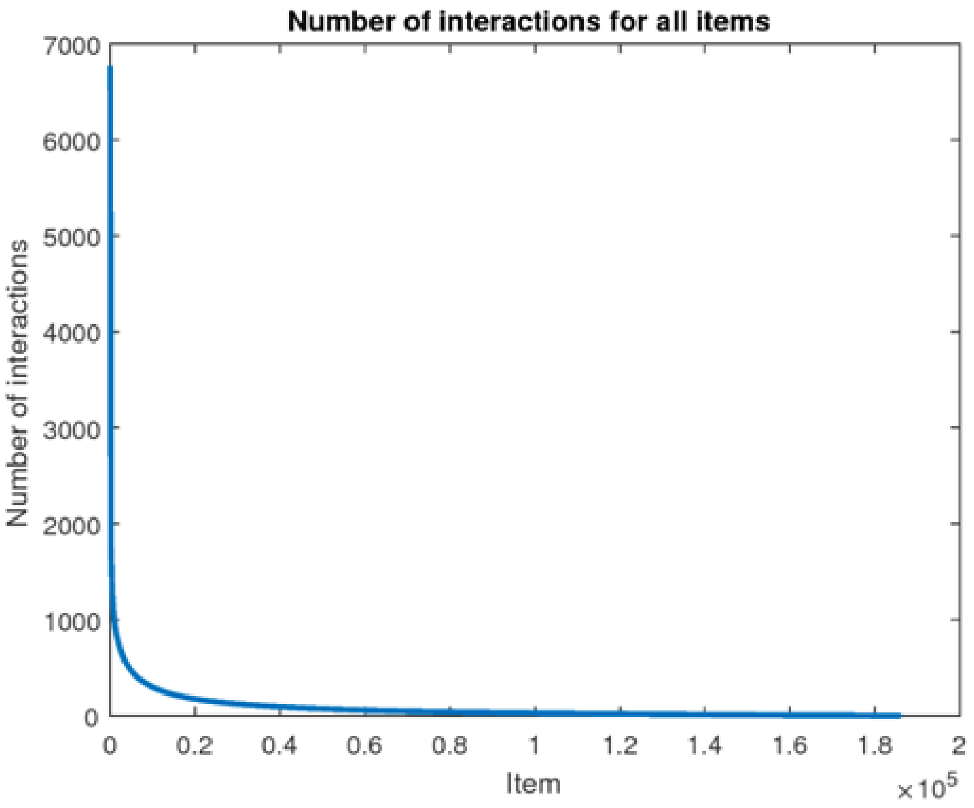
- Something similar to the ratings a user would assign, generated from observations available to the system
  - E.g., views, clicks, purchases, likes, shares etc.
- Easier to collect though less accurate in reflecting user tastes

Cold-start problem

- The system cannot draw any inferences for users or items about which it has not yet gathered sufficient information.

Number of user interactions associated to each item in the Movielens dataset.
Few items have a very high number of interactions, more than 5000, while most of the others have less than 100.

Image credit



Cold-start problem

- New community
  - This refers to the start-up of the recommender, when, although a catalogue of items might exist, almost no users are present.
- New item
  - A new item is added to the system, it might have some content information, but no interactions are present.
- New user
  - A new user registers and has not provided any interaction yet.

Approaches to Collaborative filtering

- **k-Nearest Neighbors**
- Association rules
- Matrix factorization
- Deep networks

List of references

- Bing Liu. 2007. *Web Data Mining-Exploring Hyperlinks, Contents, and Usage Data.* Springer Series on Data-Centric Systems and Applications. **Chapter 12.4**.
- Math 77B: Collaborative Filtering, Chapter 02

  https://www.math.uci.edu/icamp/courses/math77b/lecture_12w/

Exercises

1. Recommendation strategies

- John wants to build a recommender system for a recently opened online bookstore. The bookstore has over 1 million titles, yet there are only 10,000 ratings. Which strategy will work best in this scenario, c*ontent-based recommendation, user-based collaborative filtering, or item-based collaboration filtering*? Justify your answer.
- A user has rated 5/5 stars for both titles, “Linear Algebra” and “Differential Equations”. Which of the following titles has least possibility to be recommended by the above system? Justify your answer.
    a) “Operating Systems”
    b) “Convex Optimization”
    c) “Harry Potter: The Goblet of Fire”
    d) Not sure. It depends on the ratings of other users.