introduction to recommender systems

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(adapted from materials from the book
"Recommender Systems – An Introduction" by
Dietmar Jannach, Markus Zanker, Alexander Felfernig, Gerhard Friedrich
Cambridge University Press)

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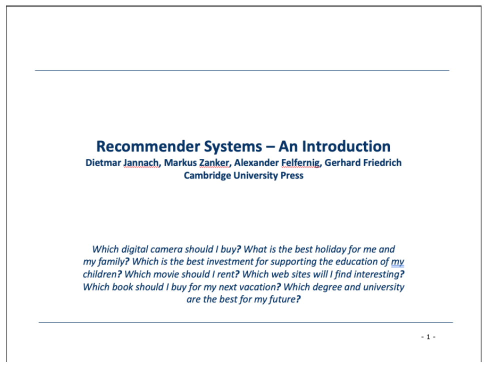
Recommender Systems – An Introduction
Dietmar Jannach, Markus Zanker, Alexander Felfernig, Gerhard Friedrich
Cambridge University Press

Which digital camera should I buy? What is the best holiday for me and my family? Which is the best investment for supporting the education of my children? Which movie should I rent? Which web sites will I find interesting? Which book should I buy for my next vacation? Which degree and university are the best for my future?

- 1 -

reference materials

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- JMM et al. ch. 13.2

plan

- introduction to RS
  - what are RS
  - differences to other ML problems: the obvious
  - UB collaborative filtering: a basic algorithm
  - evaluation
- paradigms for RS algorithms
- differences to other ML problems: the not so obvious

RS: definition

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- given
  - user model
    - e.g. ratings, preferences, demographics, situational context
  - items
    - with or without description of item characteristics
- find
  - relevance score for set of items
    - typically used for ranking

Purpose and success criteria

- retrieval
  - users know in advance what they want
  - should provide “correct”/“relevant” proposals
  - reduce search costs
- recommendation
  - items “unknown” to users
  - serendipity
- prediction
  - estimate degree of interest of users in item
- interaction
  - give users a "good feeling"
  - convince/persuade users - explain
- conversion
  - increase "hit", "clickthrough", "lookers to bookers" rates
  - optimize sales margins and profit

differences to other ML problems: the obvious

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what's the target?!

User\Item	Item 1	Item 2	Item 3	Item 4	...	....	Item N-2	Item N-1	Item N
User 1	1		1						
User 2				1				1	
User 3	1		1		1		1		
User 4									1
...									
...	1			1					
User M-2						1			
User M-1									1
User M		1				1			

very sparse

https://github.com/CSKrishna/Recommender-Systems-for-Implicit-Feedback-datasets

user-based nearest-neighbor CF: example

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	Item1	Item2	Item3	Item4	Item5
Alice	5	3	4	4	?
User1	3	1	2	3	3
User2	4	3	4	3	5
User3	3	3	1	5	4
User4	1	5	5	2	1

sim = 0,85
sim = 0,00
sim = 0,70
sim = -0,79

gps

- introduction to RS
  - what are RS
  - differences to other ML problems: the obvious
  - UB collaborative filtering: a basic algorithm
  - evaluation
    - offline evaluation
    - metrics
    - online evaluation
- paradigms for RS algorithms
- differences to other ML problems: the not so obvious

offline evaluation method

- data
  - collected in your problem
  - benchmark datasets

User\Item	Item 1	Item 2	Item 3	Item 4	...	....	Item N-2	Item N-1	Item N
User 1	1		1						
User 2				1				1	
User 3	1		1		1		1		
User 4									1
...									
...	1			1					
User M-2						1			
User M-1									1
User M		1				1			

train and test

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- training set
  - randomly selected share of known **ratings**
  - build the model
- testing set
  - remaining share of withheld ratings
  - ground truth to evaluate the model's quality
  - … by comparing with its recommendations

User\Item	Item 1	Item 2	Item 3	Item 4	...	....	Item N-2	Item N-1	Item N
User 1	1		1						
User 2				1				1	
User 3	1		1		1		1		
User 4									1
...									
...	1			1					
User M-2						1			
User M-1									1
User M		1				1			

- perhaps taking time into account rather than randomly

… maybe with a twist

- training set
  - randomly selected share of known **users**
  - build the model
- testing set
  - remaining share of withheld users
  - recommendations based on observed items
  - … compared to hidden itens

- perhaps taking time into account rather than randomly
- … and removing useless data

User\Item	Item 1	Item 2	Item 3	Item 4	…	….	Item N-2	Item N-1	Item N
User 1	1		1						
User 2				1				1	
User 3	1		1		1		1		
User 4									1
…	1			1					
User M-2						1			
User M-1									1
User M		1				1			

metrics for relevance prediction

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- confusion matrix & friends
  - borrowing from information retrieval (IR)

		Reality	
		Actually Good	Actually Bad
Prediction	Rated Good	True Positive (tp)	False Positive (fp)
	Rated Bad	False Negative (fn)	True Negative (tn)

ranks matter!

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For a user:

Actually good
Item 237
Item 899

hit

Recommended (predicted as good)
Item 345
Item 237
Item 187

- take the positions of correct items in a ranked list into account
  - as they say: “the best place to hide a corpse in the second page of results of a google search”

metrics for rating prediction

- ground truth = ratings
  - i.e. regression problem
- Mean Absolute Error (MAE) computes the deviation between predicted ratings and actual ratings

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | p_i - r_i |$$

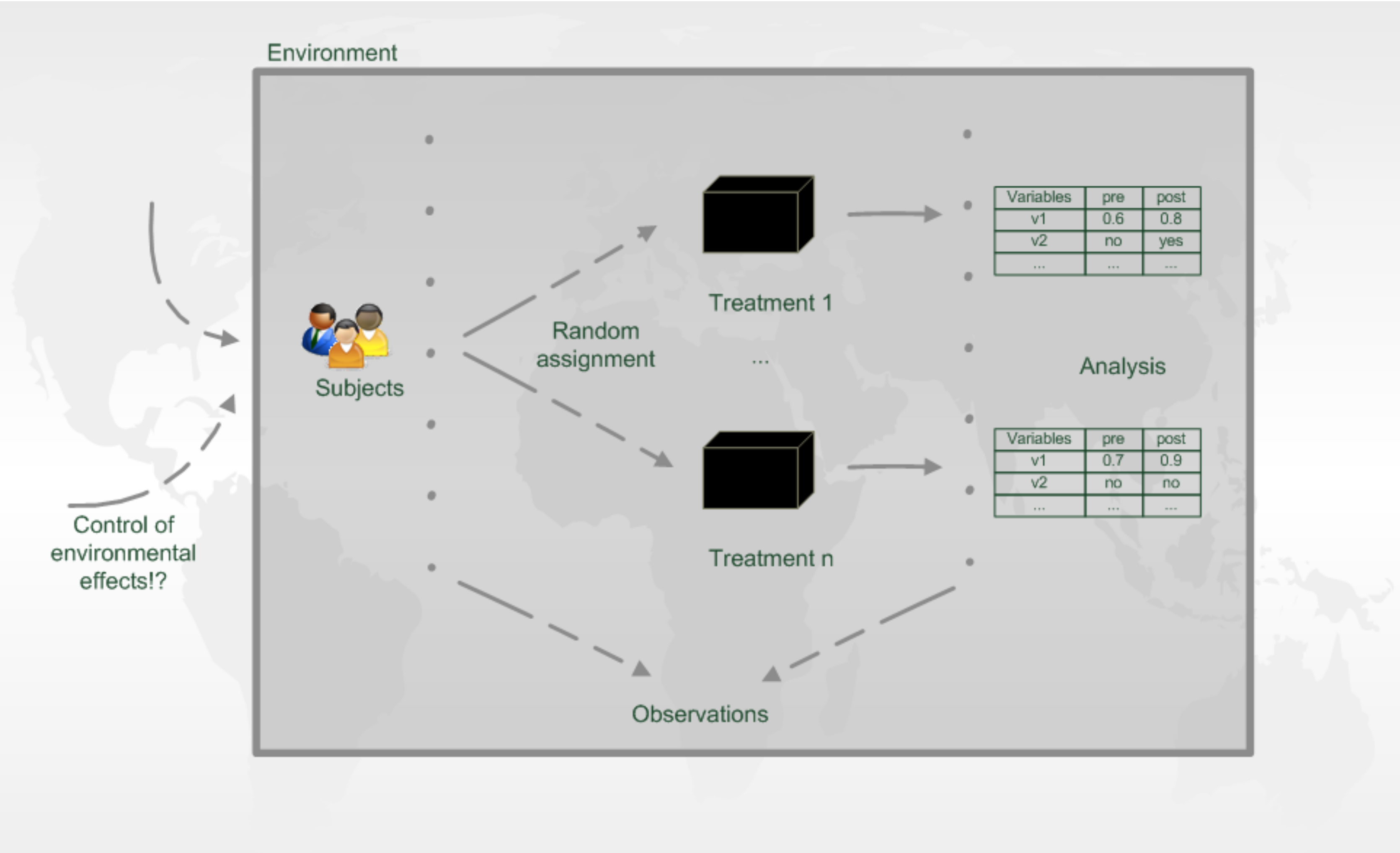
- Root Mean Square Error (RMSE) is similar to MAE, but places more emphasis on larger deviation

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(p_i - r_i)^2}$$

online evaluation

Lab studies	Field studies
• Expressly created for the purpose of the study • Extraneous variables can be controlled more easily by selecting study participants • ... who should behave as they would in a real-world environment • … but doubts may exist about participants motivated by money, prizes or social pressure	• Conducted in a preexisting real-world enviroment • Users are intrinsically motivated to use a system

Experiment designs



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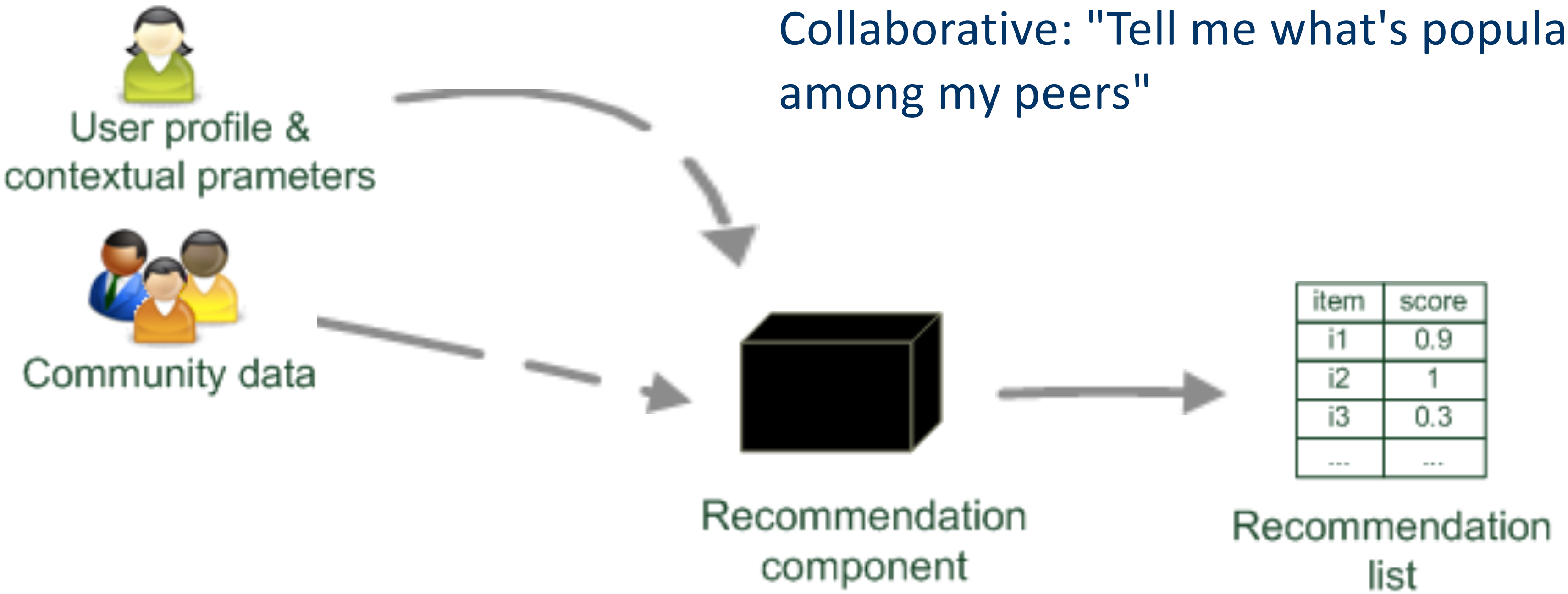
- introduction to RS
- paradigms for RS algorithms
  – collaborative
  – content
  – knowledge
  – hybrid
- differences to other ML problems: the not so obvious

Paradigms of recommender systems

Collaborative: "Tell me what's popular among my peers"



Memory-based and model-based approaches

- User-based CF is said to be "memory-based"
  – the rating matrix is directly used to find neighbors / make predictions
  – does not scale for most real-world scenarios
- Model-based approaches
  – based on an offline pre-processing or "model-learning" phase
  – at run-time, only the learned model is used to make predictions
  – models are updated / re-trained periodically

Item-based collaborative filtering

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- Basic idea:
  – Use the similarity between items (and not users) to make predictions
- Example:
  – Look for items that are similar to Item5
  – Take Alice's ratings for these items to predict the rating for Item5

	Item1	Item2	Item3	Item4	Item5
Alice	5	3	4	4	?
User1	3	1	2	3	3
User2	4	3	4	3	5
User3	3	3	1	5	4
User4	1	5	5	2	1

Matrix factorization

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- (Golub and Kahan 1965) a given matrix M can be decomposed into a product of three matrices as follows

$$M = U \times \Sigma \times V^T$$

  – where U and V are called *left* and *right singular vectors* and the values of the diagonal of Σ are called the *singular values*
- full matrix can be approximated by observing only the most important features
  – those with the largest singular values

Example for SVD-based recommendation

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- SVD: $M_k = U_k \times \Sigma_k \times V_k^T$

U_k	Dim1	Dim2
Alice	0.47	-0.30
Bob	-0.44	0.23
Mary	0.70	-0.06
Sue	0.31	0.93

V_k^T	Terminator	Die Hard	Twins	Eat Pray Love	Pretty Woman
Dim1	-0.44	-0.57	0.06	0.38	0.57
Dim2	0.58	-0.66	0.26	0.18	-0.36

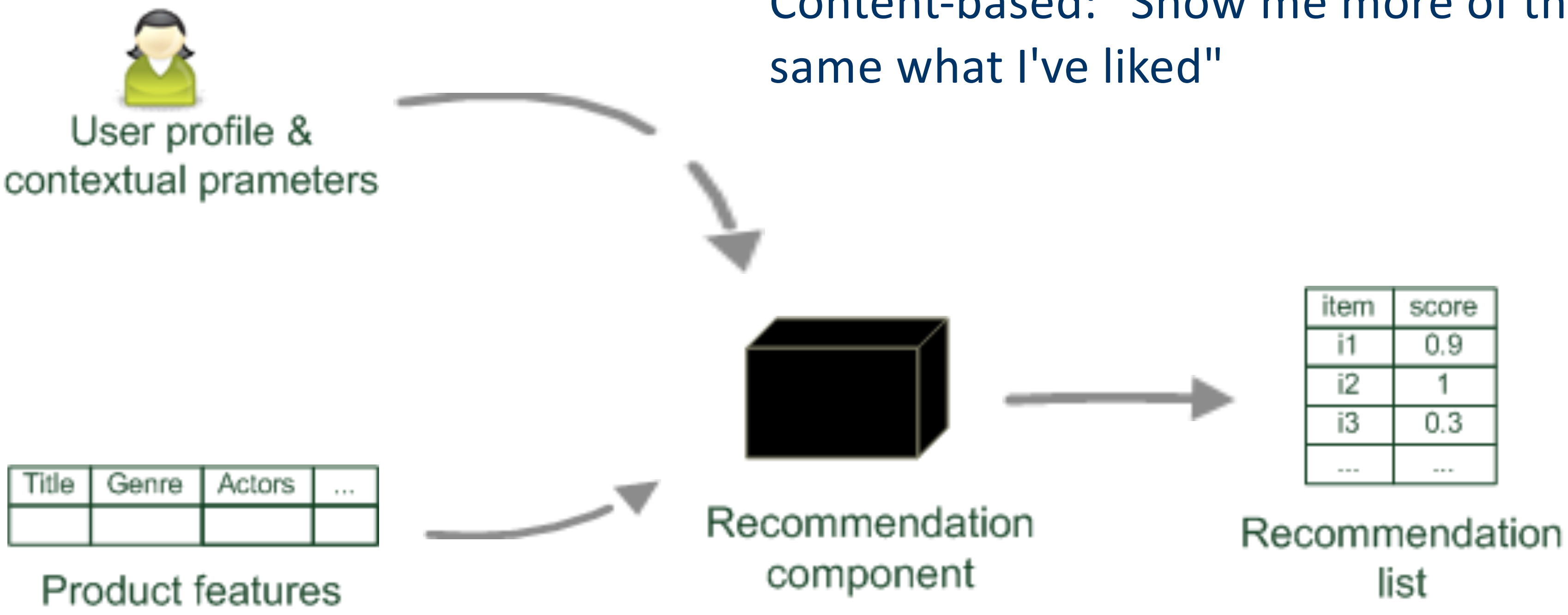
Σ_k	Dim1	Dim2
Dim1	5.63	0
Dim2	0	3.23

- Prediction: $\hat{r}_{ui} = \bar{r}_u + U_k(Alice) \times \Sigma_k \times V_k^T(EPL)$

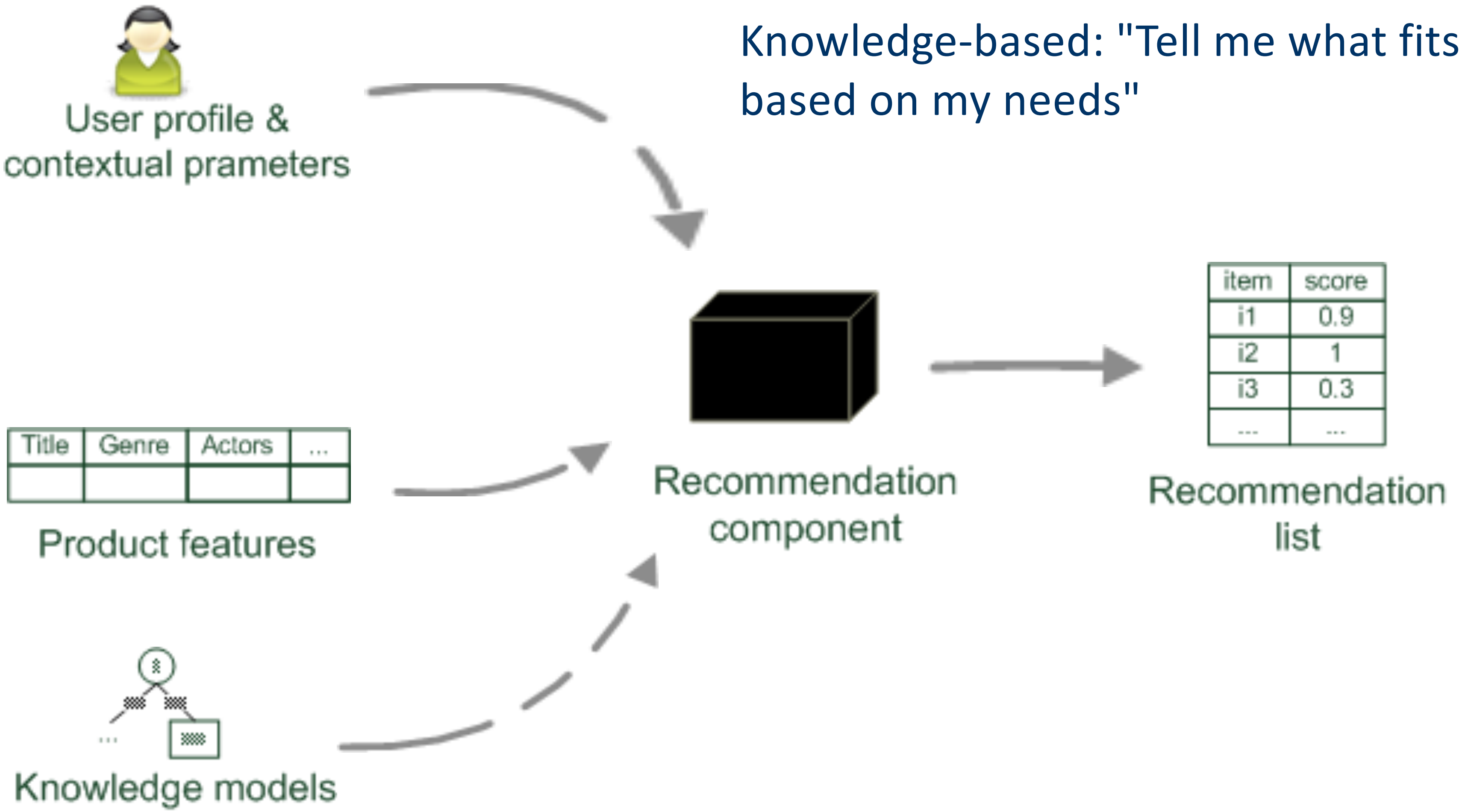
  = 3 + 0.84 = 3.84

Paradigms of recommender systems

Content-based: "Show me more of the same what I've liked"



Knowledge-based: "Tell me what fits based on my needs"



knowledge-based recommendations

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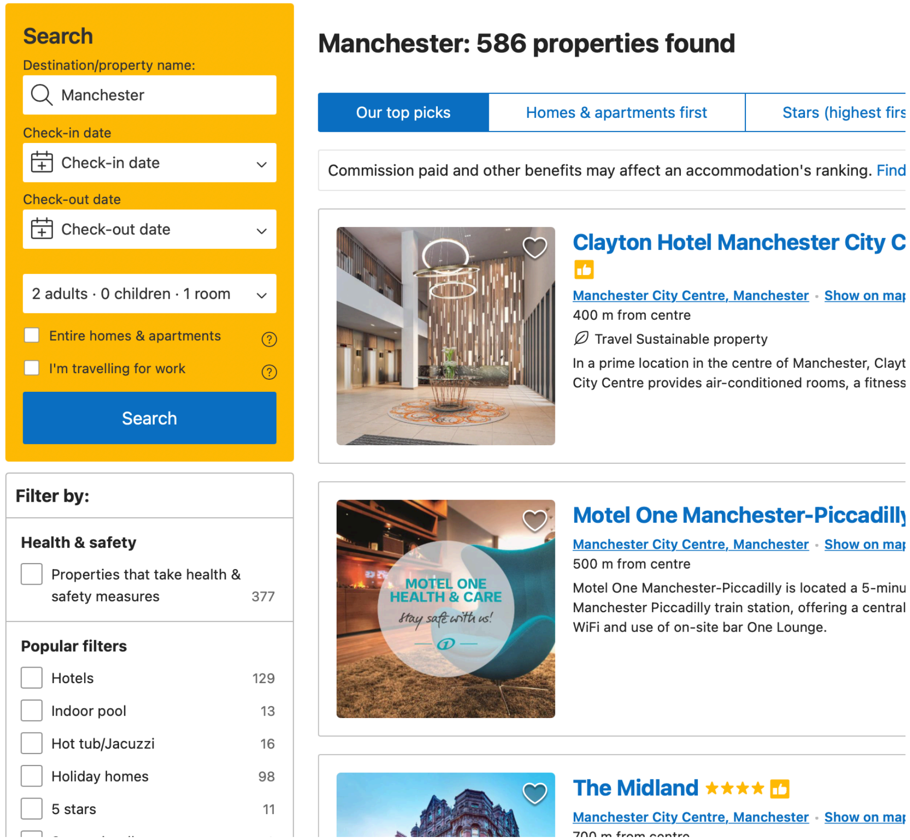
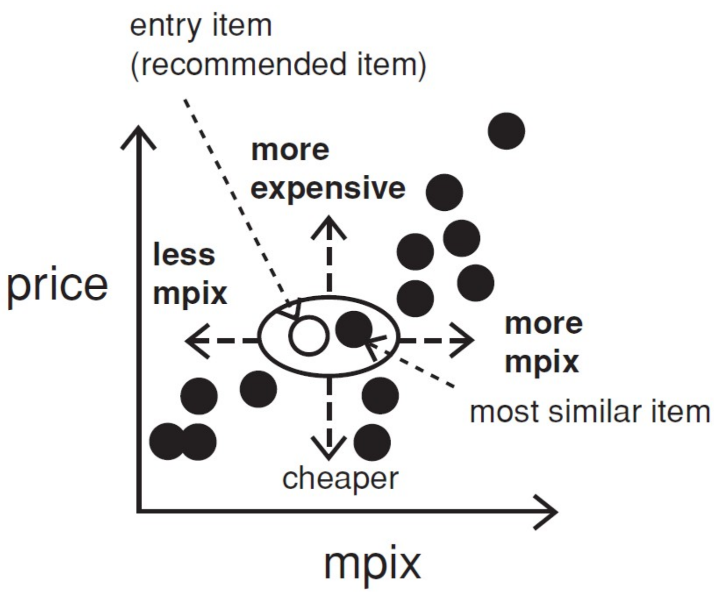
- users want to define their requirements explicitly
  - "the accomodations should be pet-friendly"
- very specific to this particular search
  - i.e. only very specific parts of profile are relevant
- usually conversational recommendation processes
  - users specify the requirements
  - systems try to identify solutions
  - if no solution can be found, users change requirements

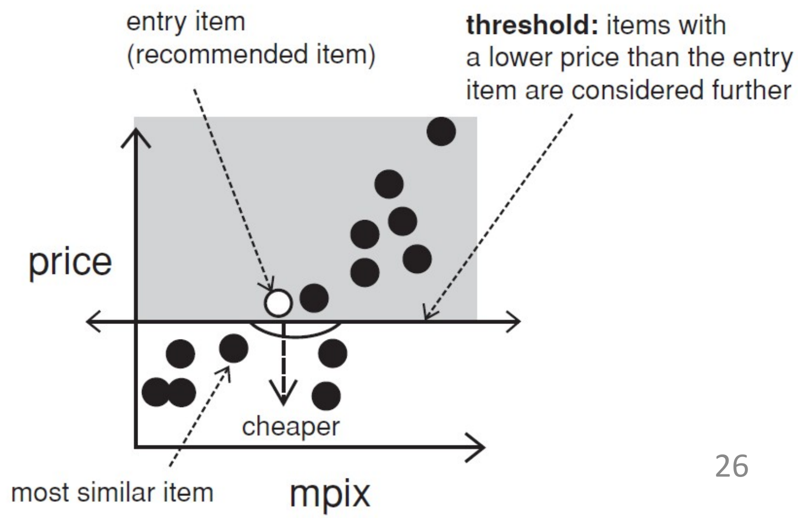


interaction with knowledge-based RS: critiquing

- user may not know exactly what they are seeking
- … can specify their why current item is not satisfactory
  - e.g. price must be lower

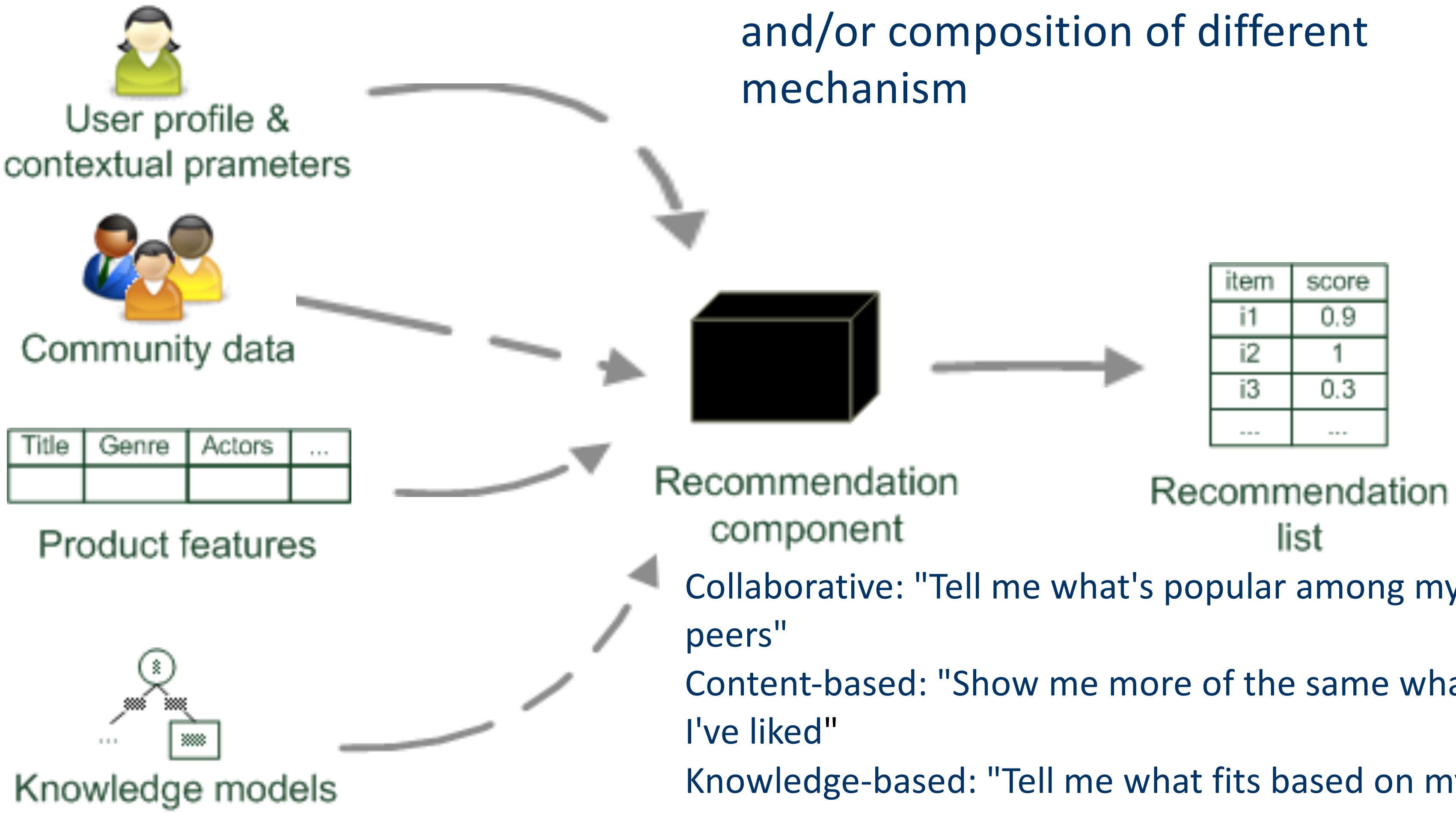


Critique on price



Hybrid recommender systems

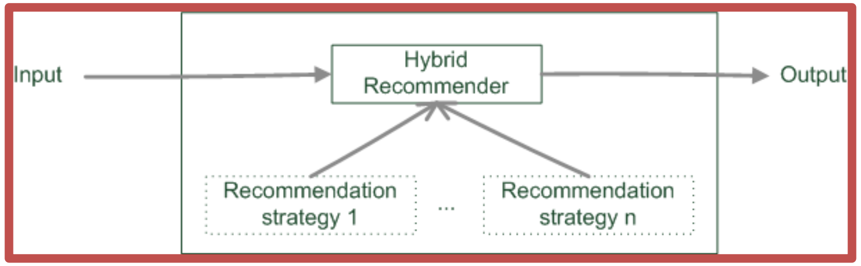
Hybrid: combinations of various inputs and/or composition of different mechanism



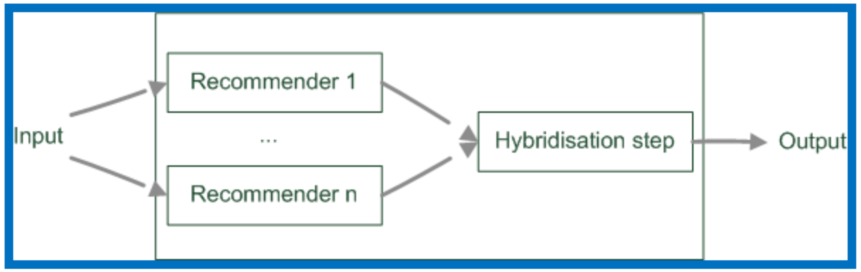
Collaborative: "Tell me what's popular among my peers"
Content-based: "Show me more of the same what I've liked"
Knowledge-based: "Tell me what fits based on my needs"

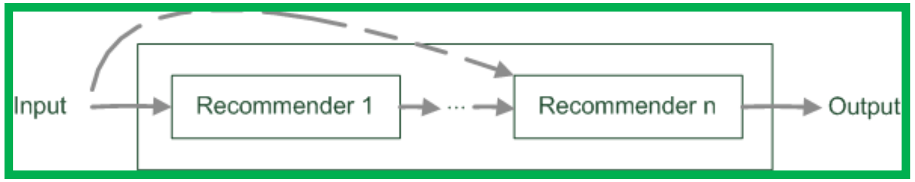
hybrid recommender systems

- think of the best salesperson you have met
  - probably combines ideas from the three approaches discussed



- hybridization
  - monolithic exploitation of different features
  - parallel
  - pipeline





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- introduction to RS
- paradigms for RS algorithms
- differences to other ML problems: the not so obvious
  - user bias
  - meaning of data
  - the long tail
  - cold start

UBCF:
not so simple after all...

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	Item1	Item2	Item3	Item4	Item5	
Alice	5	3	4	4	?	
User1	3	1	2	3	3	sim = 0,85
User2	4	3	4	3	5	sim = 0,00
User3	3	3	1	5	4	sim = 0,70
User4	1	5	5	2	1	sim = -0,79

$$pred(u,p) = \boxed{\overline{r_a}} + \frac{\sum_{b \in N} \boxed{sim(u,b)} * (r_{b,p} - \boxed{\overline{r_b}})}{\sum_{b \in N} sim(u,b)}$$

- calculate whether the neighbors' ratings for the unseen item i are higher or lower than their average rating
- ... weight, using the similarity with the active user, u, as a weight
- add/subtract the active user's average rating

meaning of data

- explicit
  - binary
    - e.g. like
  - rating
    - 1 to 5
  - … possibly multidimensional
    - e.g. ratings for actors and sound as opposed to the movie
  - … users not always willing to rate many items
- implicit
  - user action interpreted as rating
    - e.g. access to content in social media
    - … access to product's page and/or buying it
  - easy to collect transparently, without additional effort
  - … but action doesn't necessarily have the same meaning as a rating
    - e.g. user might not like all the books he or she has bought
    - … the user also might have bought a book for someone else
- important effects on offline evaluation

User\Item	Item 1	Item 2	Item 3	Item 4	...	....	Item N-2	Item N-1	Item N
User 1	1		1						
User 2				1				1	
User 3	1		1		1		1		
User 4									1
...									
...	1			1					
User M-2						1			
User M-1									1
User M		1				1			

https://github.com/CSKrishna/Recommender-Systems-for-Implicit-Feedback-datasets

serendipity and the long tail

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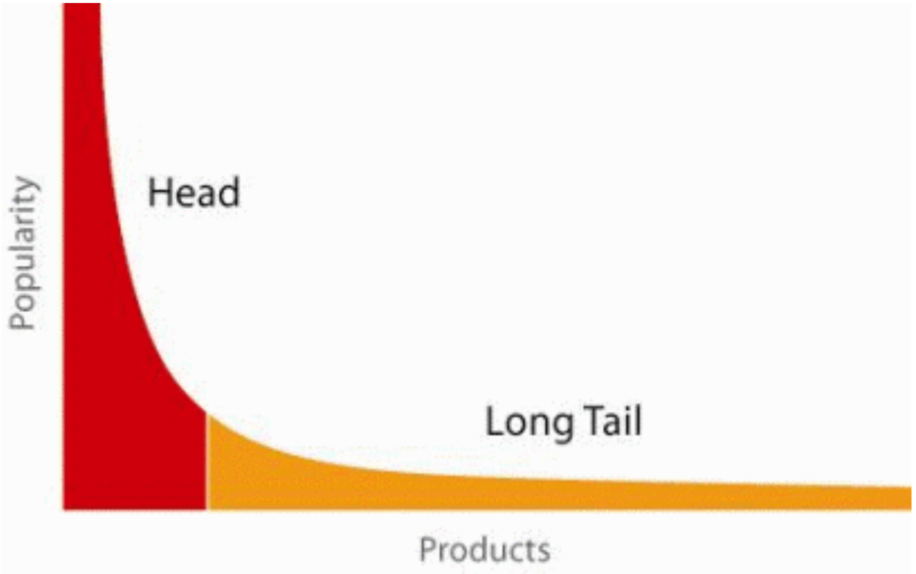
- 20% of items accumulate 74% of all positive ratings
  - less likely to be interesting recommendations
- recommend widely unknown items that users might actually like!
  - much harder



cold start

- cold start problem
  - how to recommend new items?
  - what to recommend to new users?
- some (simple) approaches
  - ask/force users to rate a set of items
  - in the beginning, use method not based on ratings
    - … then CF method
  - default voting
    - assign default values to items that only one of the two users to be compared has rated
- more complex algorithms exist

User\Item	Item 1	Item 2	Item 3	Item 4	...	....	Item N-2	Item N-1	Item N
User 1	1		1						
User 2				1				1	
User 3	1		1		1		1		
User 4									1
...									
...	1			1					
User M-2						1			
User M-1									1
User M		1				1			

https://github.com/CSKrishna/Recommender-Systems-for-Implicit-Feedback-datasets

summary

- problem of recommendation
- collaborative filtering approaches
- … and other algorithms
- evaluation is key! (once more…)
  – metrics
  – ... use of data for estimating their value
- issues of the data used in RS