UFMG UNIVERSIDADE FEDERAL DE MINAS GERAIS

Recommender Systems

Non-Personalized Collaborative Filtering

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Recommender systems

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- *"Recommender systems are software applications that aim to support users in their* ***decision-making*** *while interacting with* ***large information spaces****. They recommend* ***items*** *of interest to* ***users*** *based on* ***preferences*** *they have expressed, either explicitly or implicitly."*
  – ACM Conference on Recommender Systems

What to recommend?

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How to recommend?

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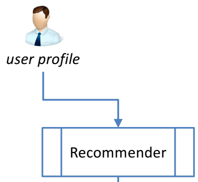

item	score
1	0.7
2	0.3
…	…

How to recommend?

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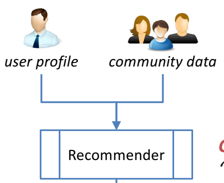

Collaborative filtering
"tell me what's popular among my peers"

item	score
1	0.7
2	0.3
…	…

How to recommend?

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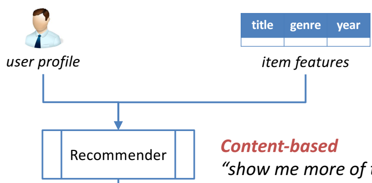

Content-based
"show me more of the same what I've liked"

item	score
1	0.7
2	0.3
…	…

How to recommend?

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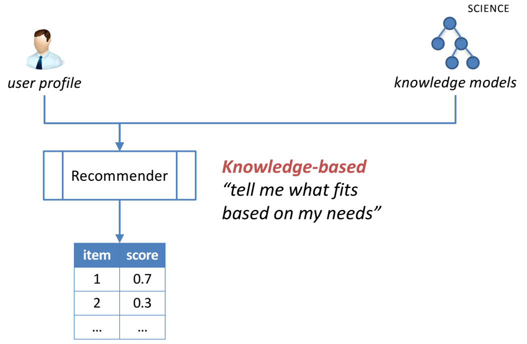

Knowledge-based
"tell me what fits based on my needs"

How to recommend?

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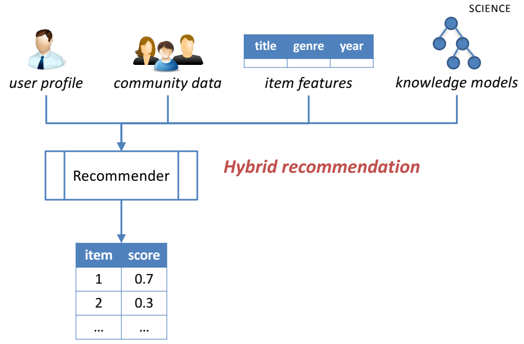

Hybrid recommendation

How to recommend?

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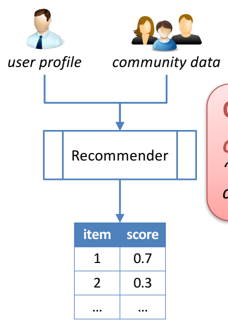

OUR FOCUS
Collaborative filtering
"tell me what's popular among my peers"

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Recommender Systems

MODELING PREFERENCES

Acquiring feedback

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- We want to know
  - What users consider relevant
- We can observe
  - What users tell us (ratings)
  - What users do (actions)
- These are *noisy measurements*
  - Relevance is a user's prerogative

Feedback model

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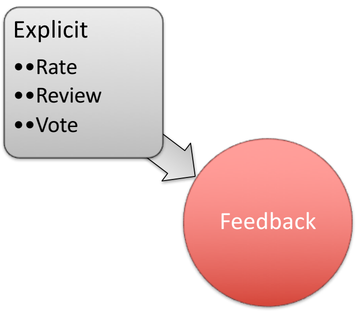

Explicit feedback

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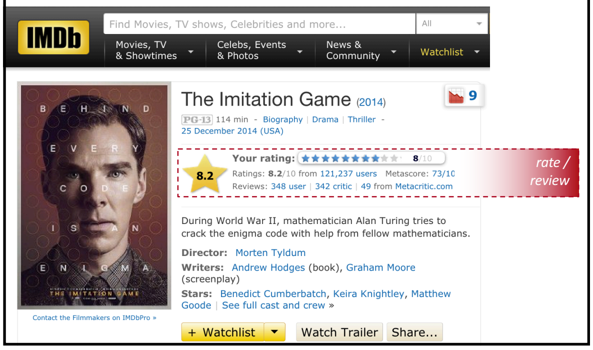

Explicit feedback

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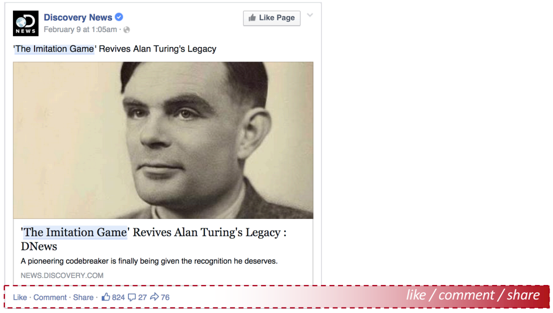

Explicit feedback

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- Are ratings reliable and accurate?
  - *Are my 8/10 stars equivalent to yours?*
- Do user preferences change?
  - *Will I still like the item after 10 years?*
- What does a rating mean?
  - *Will I ultimately consume the rated item?*

Feedback model

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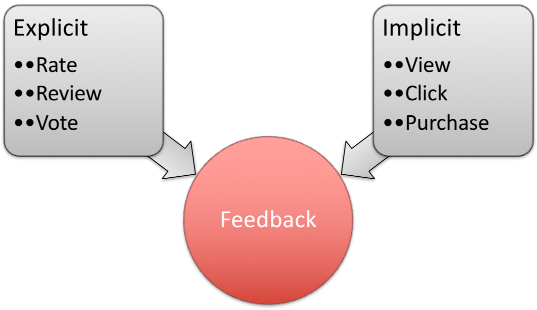

Implicit feedback

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- Abundant data from user actions
  - Views, clicks, reads, buys, etc.
- Actions typically for some other purpose
  - Not direct expressions of preference
- But actions say a lot!
  - Binary signals (click, skip, play, purchase)
  - Attention signals (reading / listening / watching)
  - Cognitive signals (eye-tracking, brain imaging)

Implicit feedback

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- What does the action mean?
  - Purchase: they might still hate it
  - Don't click: bad, or didn't see?
- How to factor in cognitive biases?
  - Position, presentation, popularity, etc.

How to leverage user feedback to produce recommendations?

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Recommender Systems

COLLABORATIVE FILTERING

Collaborative filtering (CF)

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- Most prominent recommendation approach
  - Used by large commercial e-commerce sites
  - Applicable in many domains (books, movies, etc.)
- Key idea
  - Leverage the “wisdom of the crowds”
- Basic assumption
  - Users’ future preferences can be predicted by their past preferences (acquired via feedback)

Stable preferences

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- Some examples
  - News: I prefer technology, travel
  - Music: I prefer rock, grunge, folk
  - Clothing: I prefer cotton, casual
  - Movies: I prefer sci-fi, thrillers

CF formulation

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- Input
  - A matrix of user-item ratings
    - Ratings could be either implicit or explicit
    - Items could be pretty much anything
- Output (for a target user)
  - A number indicating the user’s predicted preference for an item ***(prediction)***
  - A list of items in decreasing order of predicted preference for the user ***(top-n recommendation)***

CF formulation

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- *Predict how much user **u** will like item **i***

			i					
			1	3		2		
	1	2	5		4		1	
	4			3	5		4	
u		2	?		5	4		4
		3	4		5		3	

buys
clicks
views
rates
reviews
…

CF formulation

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- *Recommend items that user **u** will like*

			1	3		2		
	1	2	5		4		1	
	4			3	5		4	
u	?	2	?	?	5	4	?	4
		3	4		5		3	

buys
clicks
views
rates
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…

CF formulation

- *What if we know nothing about user u?*

			i					
			1	3		2		
	1	2	5		4		1	
	4			3	5		4	
u			?					
		3	4		5		3	

Non-personalized CF

- *What if we know nothing about user u?*

			i					
			1	3		2		
	1	2	5		4		1	
	4			3	5		4	
u			3.3					
		3	4		5		3	

We can use the average rating!

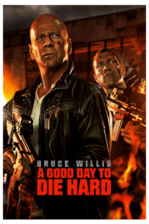
$$\hat{r}_{ui} = \frac{1}{|U_i|} \sum_{x \in U_i} r_{xi}$$

$$\hat{r}_{ui} = \frac{1}{3}(1+5+4)$$

$$\hat{r}_{ui} = 3.33$$

Non-personalized CF

- Problem?
  - Predicted utility of *i* will be the same for all users



Non-personalized CF

- Problem?
  - Predicted utility of *i* will be the same for all users
- Solution
  - We could compute a segmented average
    - e.g., by age, gender, income, location
  - Better, but still not fully personalized
    - Prediction will be the same for a given segment

Non-personalized CF

- Problem?
  - Predicted utility of *i* ignores context

Non-personalized CF

- Problem?
  - Predicted utility of *i* ignores context
- Solution
  - We could compute non-personalized associations
    - e.g., what sauce goes along with ice cream?
  - Great, but what associations to leverage?
    - ***Historical profiles*** may introduce spurious associations
    - ***Transaction data*** may limit follow-up sales
    - ***Time-constrained profiles*** offer a compromise

Associative recommendations

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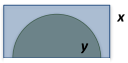
- Start simple
  - Percentage of ***x***-buyers who also bought ***y***

$$\hat{r}_{uy} \propto \frac{f(x \wedge y)}{f(x)}$$



- Problem:
  - What if ***y*** is extremely popular?

Associative recommendations

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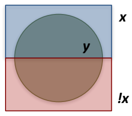
- Start simple
  - Percentage of ***x***-buyers who also bought ***y***

$$\hat{r}_{uy} \propto \frac{f(x \wedge y)}{f(x)}$$



- Problem:
  - What if ***y*** is extremely popular?

Associative recommendations

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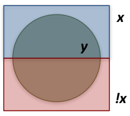
- Take two
  - Does ***x*** make ***y*** more likely?

$$\hat{r}_{uy} \propto \left[\frac{f(x \wedge y)}{f(x)} \Big/ \frac{f(!x \wedge y)}{f(!x)} \right]$$



- Intuitively:
  - Is ***y*** more likely with ***x*** than without it?

Associative recommendations

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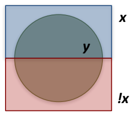
- More generally
  - Does ***x*** make ***y*** more likely?

$$\hat{r}_{uy} \propto \frac{p(x \cap y)}{p(x)p(y)}$$



- Intuitively:
  - Are ***x*** and ***y*** more likely to occur together than separately? (aka "lift" in association rule mining)
  - Lift = 1: ***x*** and ***y*** are independent

Summary

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- Recommenders mine what users *say* and what they *do* to learn preferences
  - Ratings provide explicit expressions of preference
  - Implicit data benefits from greater volume
- Non-personalized recommenders are a good first approximation of users' preferences
  - May be the only possibility in some cases
- To go beyond, we need more data
  - Personalized recommenders