UFMG UNIVERSIDADE FEDERAL DE MINAS GERAIS

Recommender Systems

Non-Personalized Collaborative Filtering

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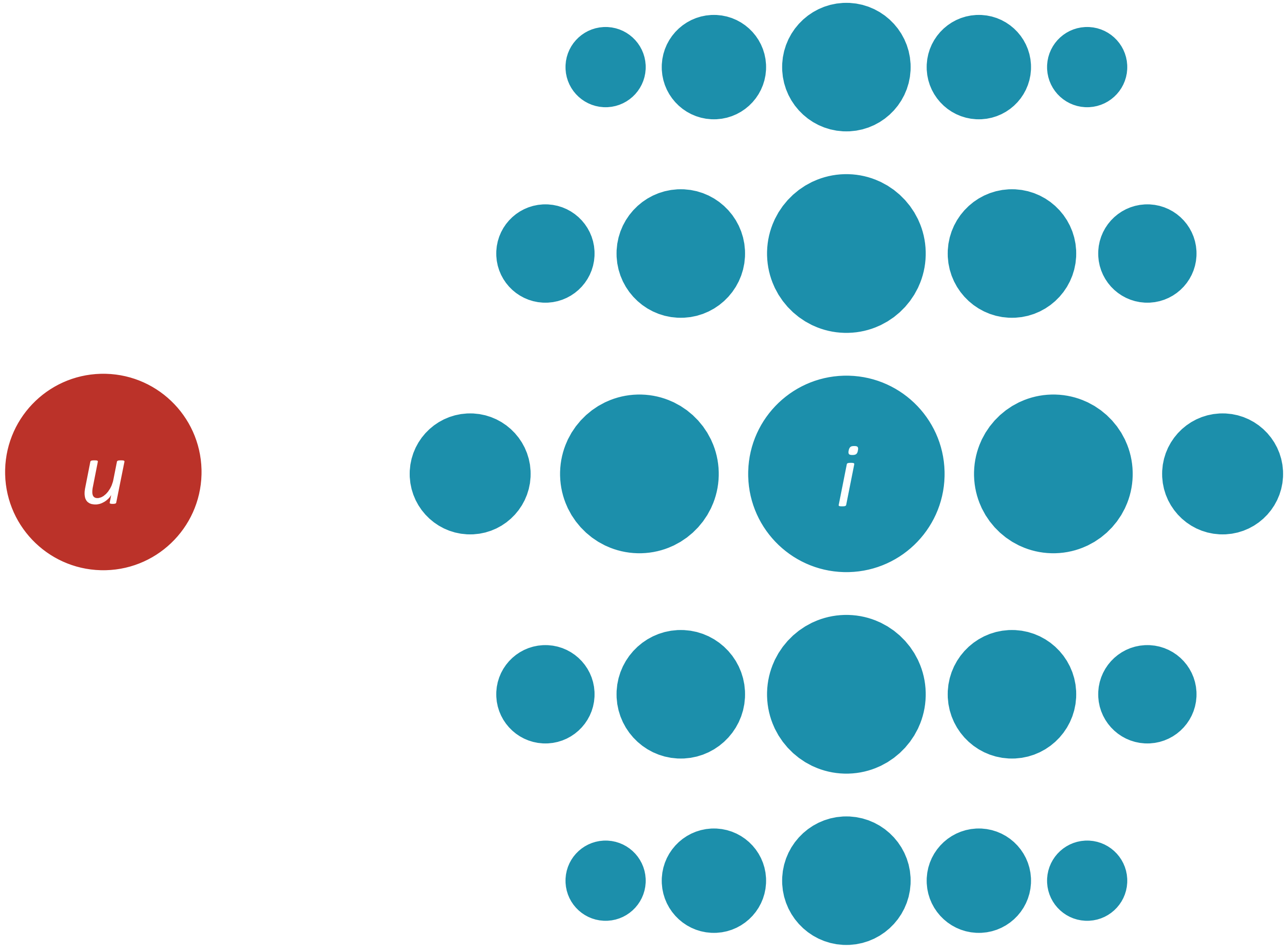
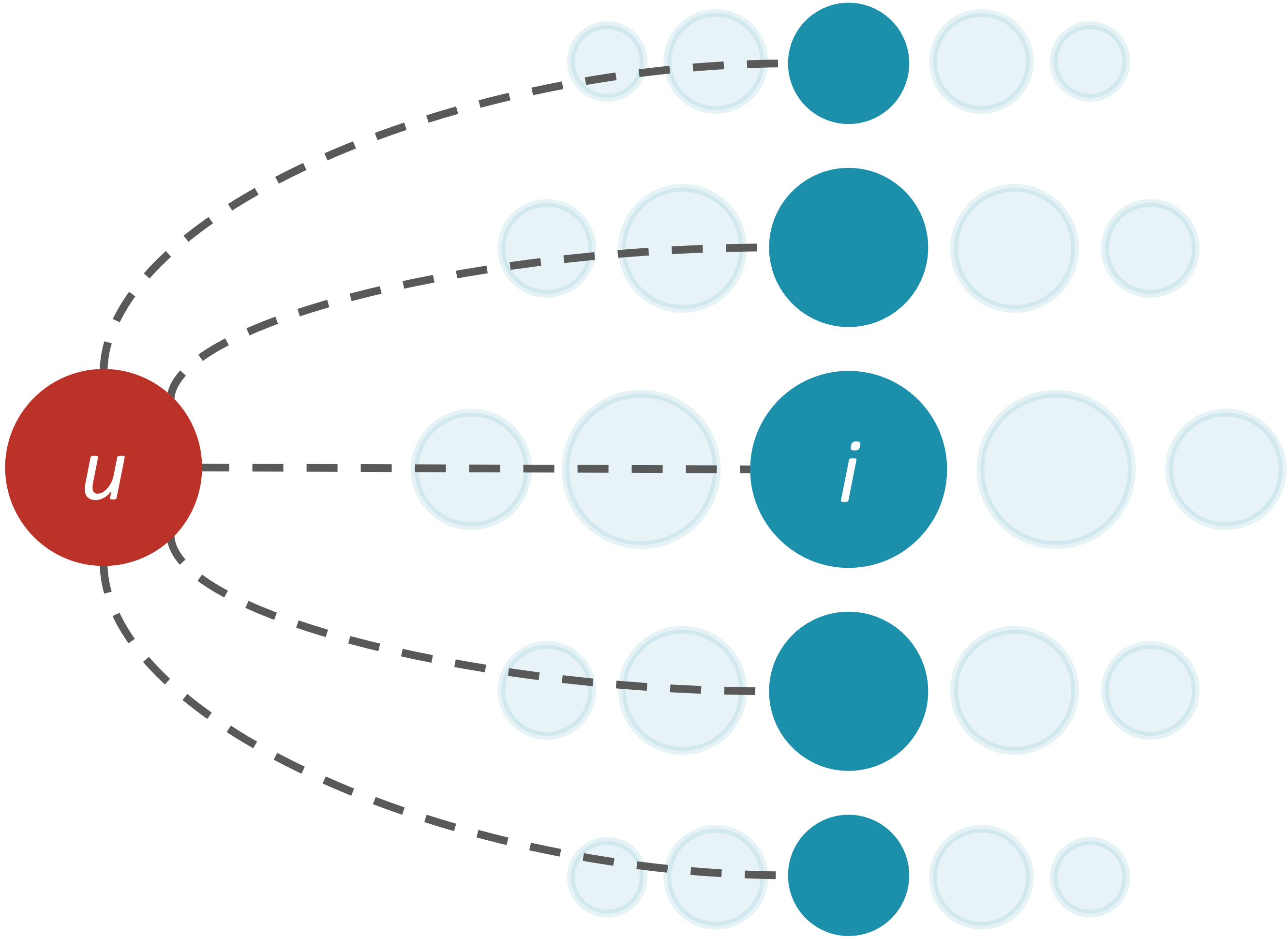
The recommendation problem

$$f(u, i)$$

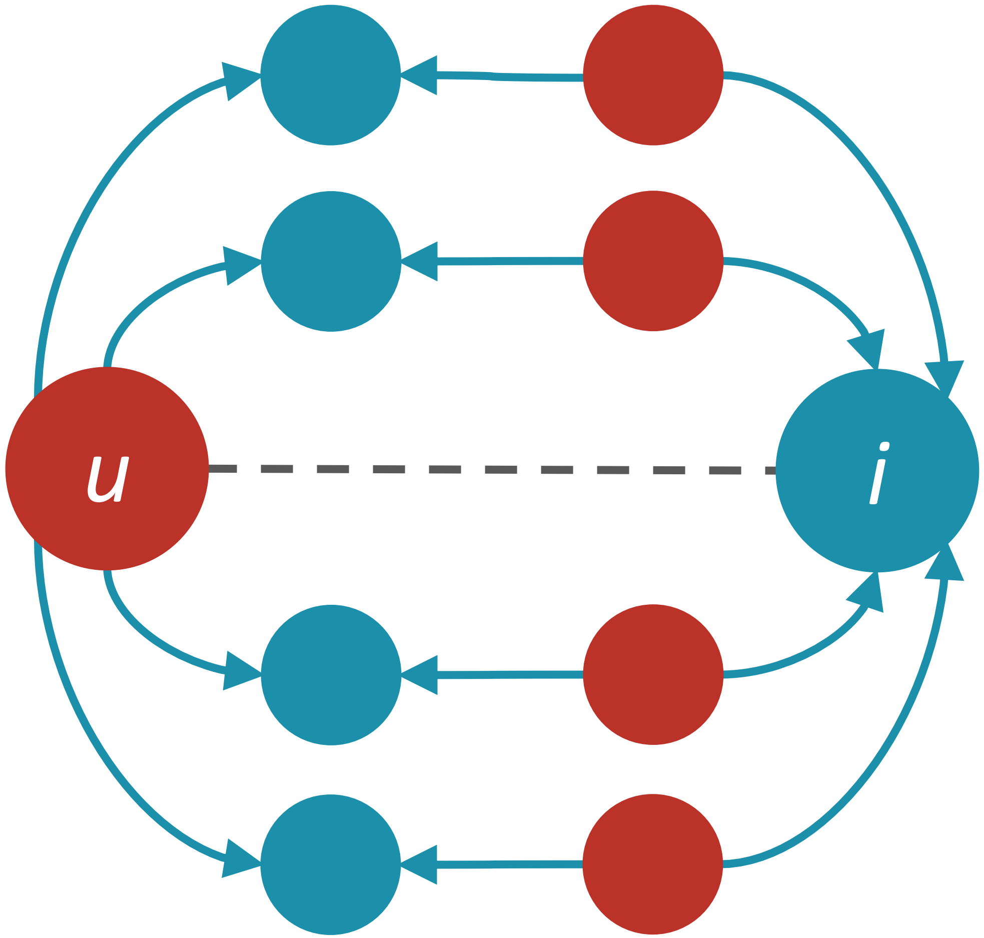
The recommendation problem



The recommendation problem



Collaborative recommendation



Collaborative recommendation

Key idea

- Leverage the "wisdom of the crowds"

Most prominent recommendation approach

- Used by large commercial e-commerce sites
- Applicable in many domains (books, movies, etc.)

Stable preferences

Basic assumption

- Past preferences indicate future preferences

Some examples

- News: I prefer technology, travel
- Music: I prefer rock, grunge, folk
- Movies: I prefer sci-fi, thrillers

Modeling preferences

We want to know

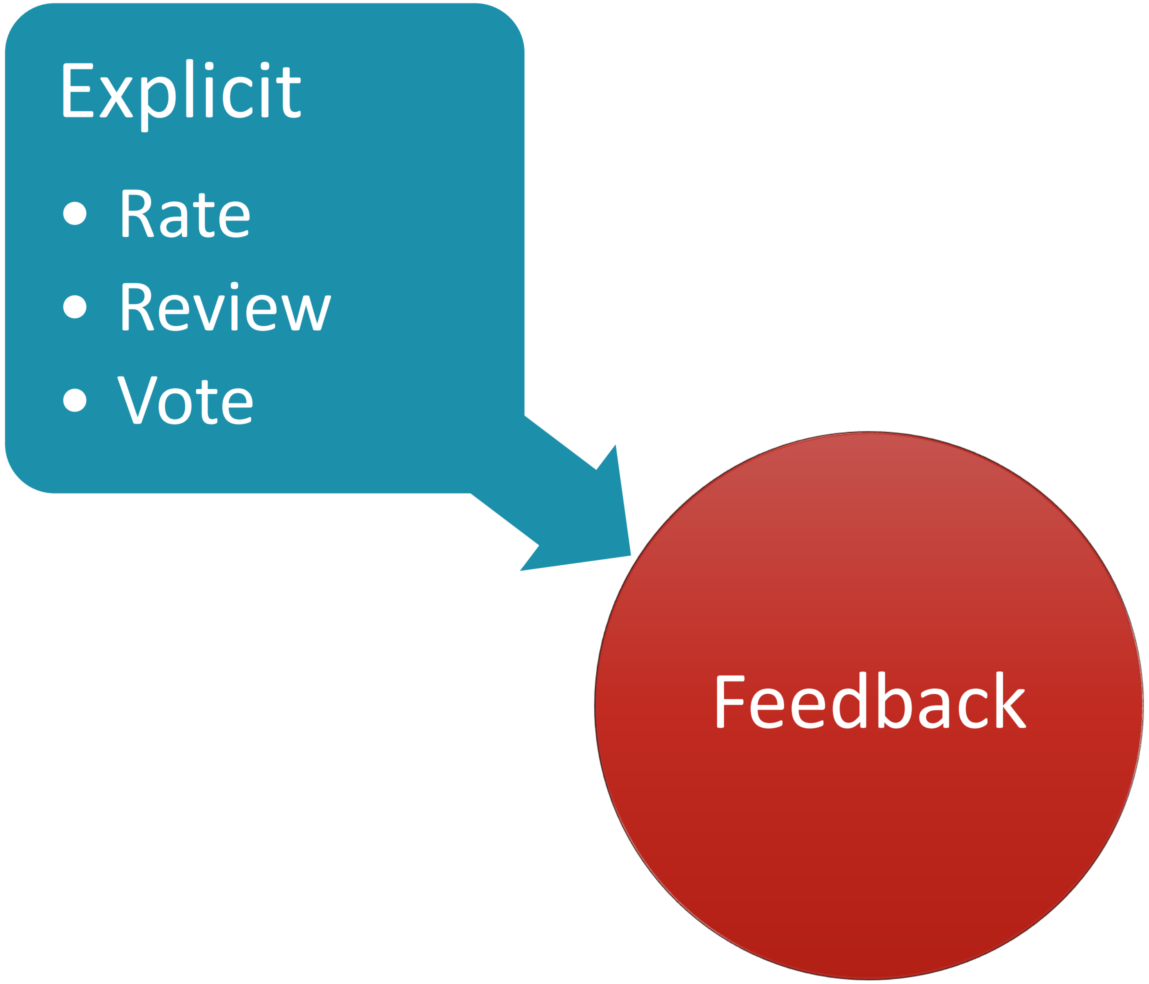
- What users consider relevant

We can observe

- What users tell us (ratings)
- What users do (actions)

These are ***noisy*** measurements

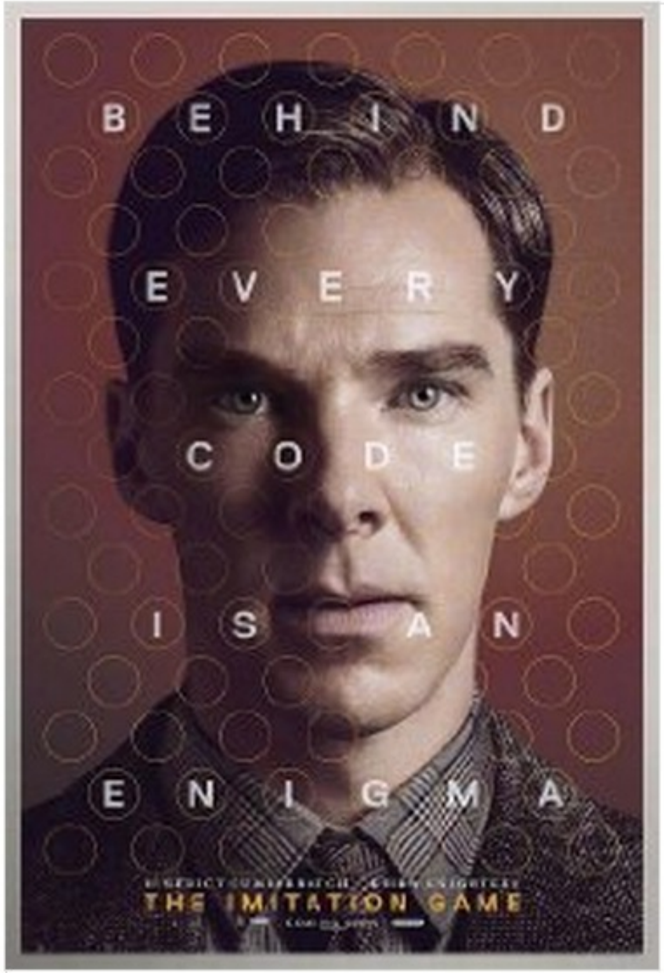
Feedback model



IMDb

Find Movies, TV shows, Celebrities and more... | All

Movies, TV & Showtimes | Celebs, Events & Photos | News & Community | Watchlist



Contact the Filmmakers on IMDbPro »

The Imitation Game (2014)

9

PG-13 114 min - Biography | Drama | Thriller - 25 December 2014 (USA)

8.2

Your rating: 8/10

Ratings: **8.2**/10 from 121,237 users Metascore: 73/100

Reviews: 348 user | 342 critic | 49 from Metacritic.com

rate / review

During World War II, mathematician Alan Turing tries to crack the enigma code with help from fellow mathematicians.

Director: Morten Tyldum

Writers: Andrew Hodges (book), Graham Moore (screenplay)

Stars: Benedict Cumberbatch, Keira Knightley, Matthew Goode | See full cast and crew »

+ Watchlist | Watch Trailer | Share...

Explicit feedback

Are ratings reliable and accurate?

- *Are my 8/10 stars equivalent to yours?*

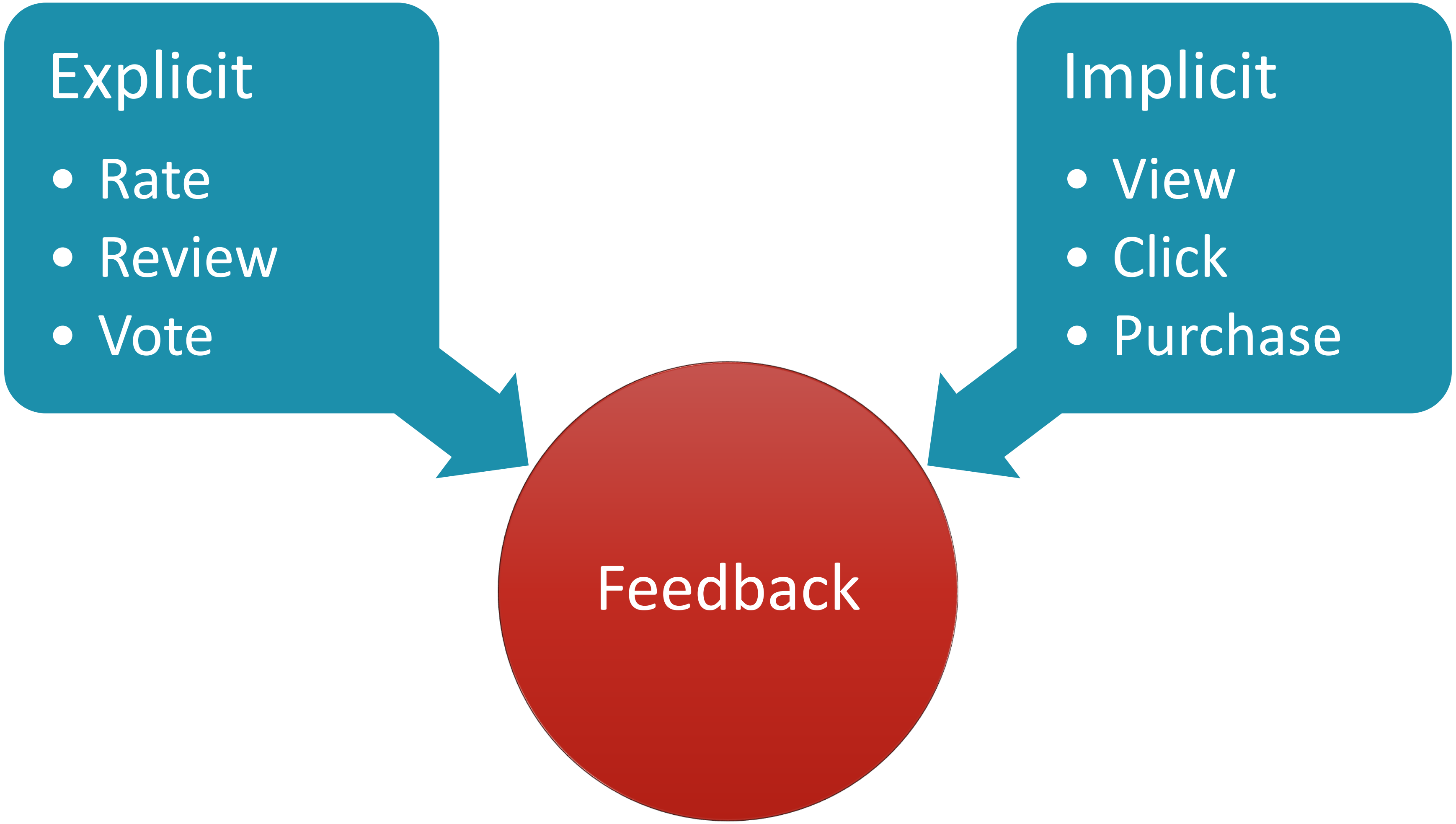
Do user preferences change?

- *Will I still like the item after 10 years?*

What does a rating mean?

- *Will I ultimately consume the rated item?*

Feedback model



Implicit feedback

Abundant data from user actions

- Not direct expressions of preference

But indirectly say a lot!

- Action signals (click, skip, play, purchase)
- Attention signals (reading, listening, viewing time)
- Cognitive signals (eye-tracking, brain imaging)

Implicit feedback

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?

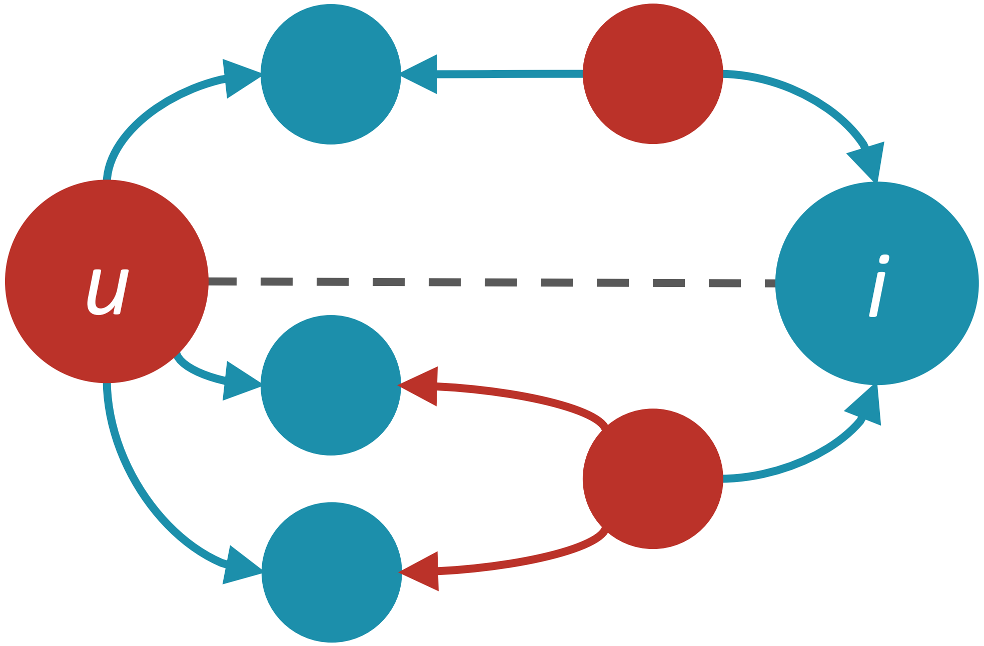
- Position, presentation, popularity, etc.

How to leverage user feedback?

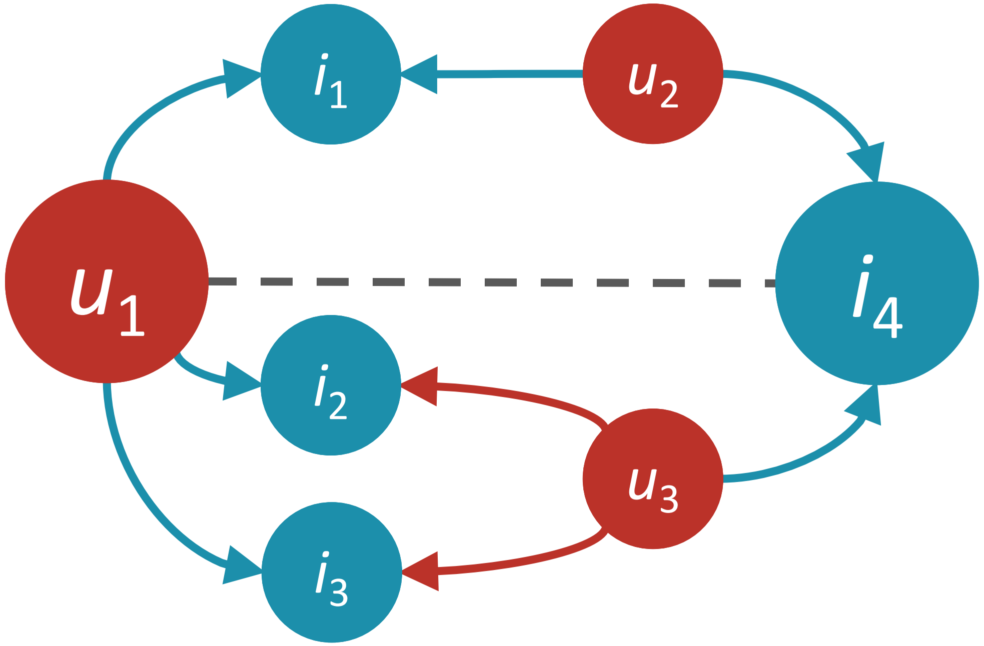
Leveraging user feedback

$$f(u, i)$$

Leveraging user feedback



Leveraging user feedback



Leveraging user feedback

	i_1	i_2	i_3	i_4
u_1	+1	+1	+1	
u_2	+1			+1
u_3				+1

unary feedback
(e.g., click)

Leveraging user feedback

	i_1	i_2	i_3	i_4
u_1	+1	+1	+1	
u_2	+1			+1
u_3		-1	-1	+1

binary feedback
(e.g., like / dislike)

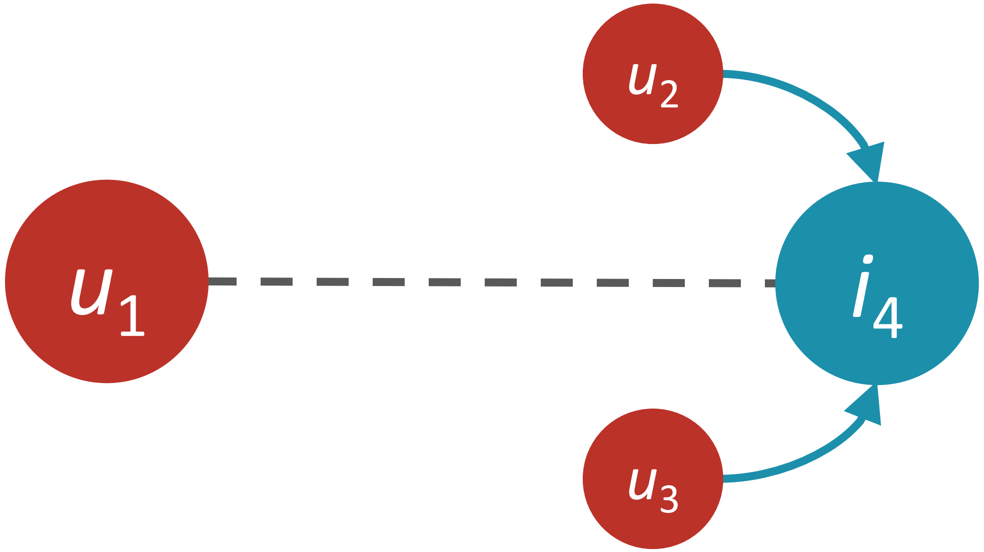
Leveraging user feedback

	i_1	i_2	i_3	i_4
u_1	5	3	3	?
u_2	5			3
u_3		1	2	1

graded feedback
(e.g., rate)

What if we don’t know the user?

Cold-start user



Cold-start user

	i_1	i_2	i_3	i_4
u_1				?
u_2	5			3
u_3		1	2	1

we can use some **global property** of the target item

Non-personalized collaborative filtering

	i_1	i_2	i_3	i_4
u_1				?
u_2				3
u_3				1

most recent
most popular
best rated

Best-rated recommendation

	i_1	i_2	i_3	i_4
u_1				?
u_2				3
u_3				1

$$\hat{r}_{u_1 i_4} = \frac{1}{|U_{i_4}|} \sum_{v \in U_{i_4}} r_{v i_4}$$

$$= \frac{1}{2}(3 + 1)$$

$$= 2$$

Most-popular recommendation

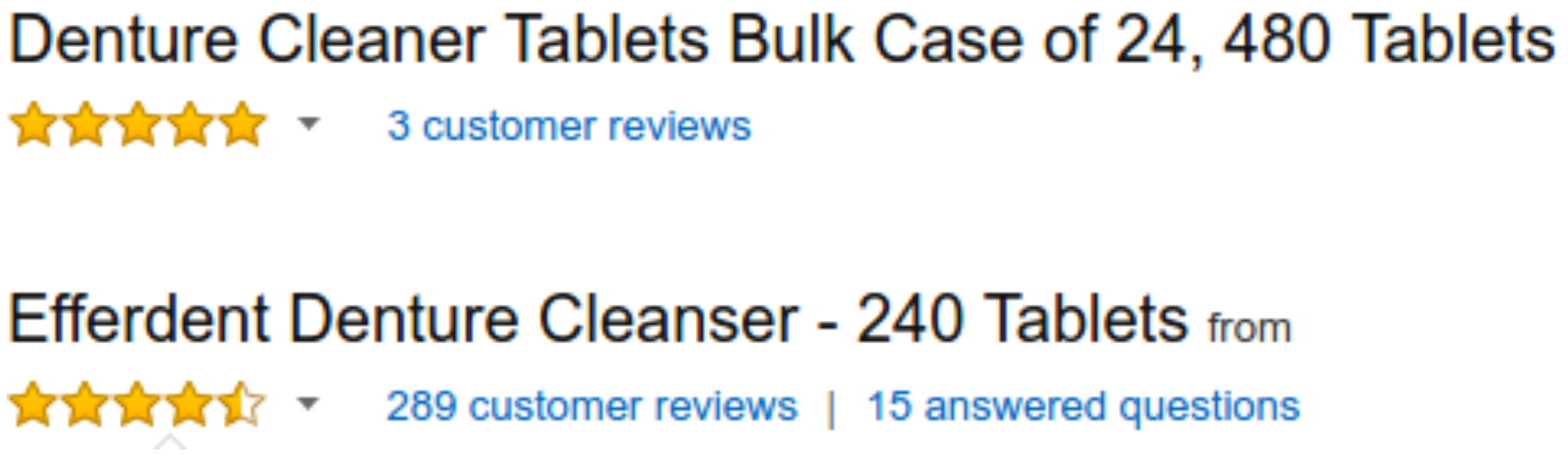
	i_1	i_2	i_3	i_4
u_1				?
u_2				3
u_3				1

$$\hat{r}_{u_1 i_4} = |U_{i_4}|$$
$$= 2$$

What could go wrong?

Problem #1: imbalanced feedback

Best rated denture cleaners
(ranked by average rating)



Problem #1: imbalanced feedback

Predicted utility of i ignores feedback imbalance

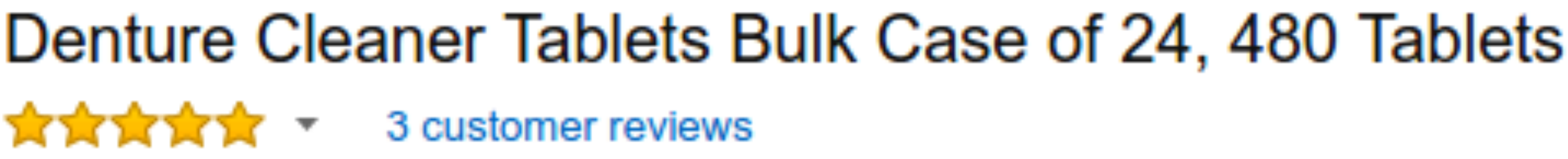
- We could add a confidence factor to balance the observed feedback with the incurred uncertainty

Typically (similar methods for proportions)

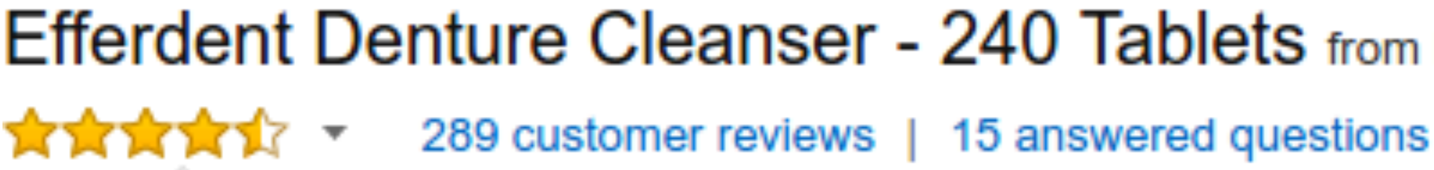
- $\hat{r}_{ui} \propto \bar{r}_i - z \frac{\sigma}{\sqrt{|U_i|}}$ (penalize proportionally to variance) (penalize inversely proportionally to sample size)

Problem #1: imbalanced feedback

Best rated denture cleaners
(ranked by average rating)



lower bound for 99% confidence: 4.26



lower bound for 99% confidence: 4.42

Problem #1: imbalanced feedback

Best rated denture cleaners

(ranked by average rating + confidence)

Efferdent Denture Cleanser - 240 Tablets from

289 customer reviews | 15 answered questions

lower bound for 99% confidence: 4.42

Denture Cleaner Tablets Bulk Case of 24, 480 Tablets

3 customer reviews

lower bound for 99% confidence: 4.26

Problem #2: user agnosticism

Most popular shows…

Problem #2: user agnosticism

Predicted utility of i will be the same for all users

- We could compute segmented statistics
  - e.g., by age, gender, income, location
- Better, but still not fully personalized
  - Prediction will be the same for a given segment

Problem #3: context agnosticism

Best rated sauce

… to go along with your ice cream?

Problem #3: context agnosticism

Predicted utility of i ignores context

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

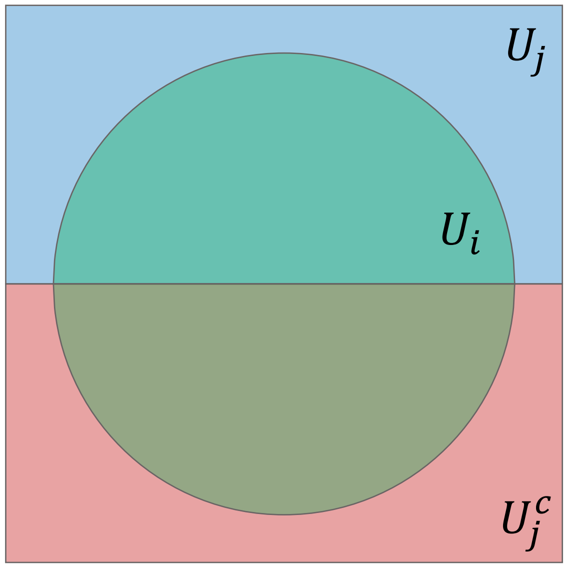
Associative recommendation

Percentage of j buyers who also bought i

- $\hat{r}_{ui} \propto \frac{|U_i \cap U_j|}{|U_j|}$

Problem:

- What if i is extremely popular?



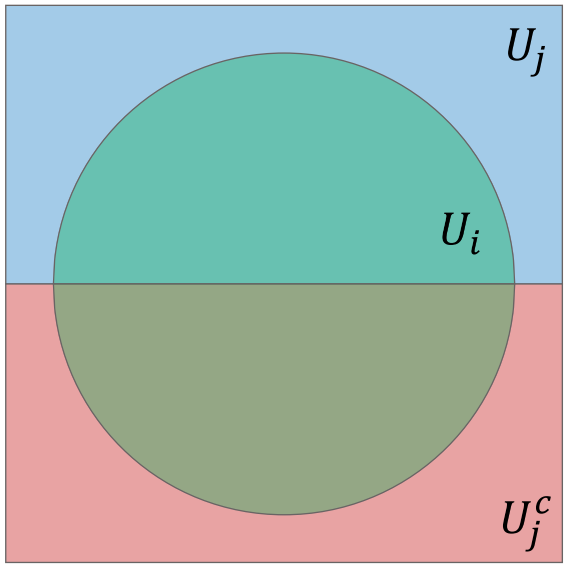
Associative recommendation

Odds of j buyers to also buy i

- $\hat{r}_{ui} \propto \frac{|U_i \cap U_j|}{|U_j|} / \frac{|U_i \cap U_j^c|}{|U_j^c|}$

Intuitively:

- Is i more likely with j than without it?



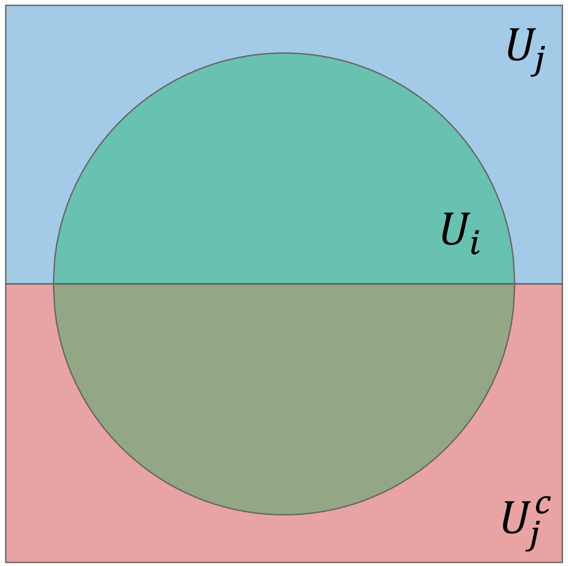
Associative recommendation

More generally:

- $\hat{r}_{ui} \propto \frac{p(i,j)}{p(i)p(j)}$ (aka "lift")

Intuitively:

- Are i and j more likely to occur together than separately?
- Lift = 1: i and j are independent



Summary

Recommenders mine what users *say* and what they *do*

- Ratings provide explicit expressions of preference
- Implicit data benefits from greater volume

Non-personalized recommenders are a good first try

- May be the only possibility in some cases

Summary

To get personal, we need more data

- Personalized recommendation models
- Preference elicitation models