UFMG UNIVERSIDADE FEDERAL DE MINAS GERAIS

Recommender Systems

Context-aware Recommendation

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Context in recommendation

Example scenario: Dan’s purchases on Amazon

- “Da Vinci Code” *................ for leisure*
- “Python Programming” *.... for work*
- “Green Eggs and Ham” *..... for his daughter*

How should we represent Dan’s interest in books?

- Must understand the ***context*** of each interaction yelp

tacos, cheap dinner, Max's | Belo Horizonte, Minas Gerais, Brazil

For Businesses | Write a Review

Restaurants | Home Services | Auto Services | More

Browsing Belo Horizonte - MG, Brazil businesses

Sort: **Recommended**

Filters

$ | $$ | $$$ | $$$$

Suggested

- [ ] Open Now 11:36 AM

Features

- [ ] Good for Groups
- [ ] Has TV
- [ ] Offers Takeout
- [ ] Good for Kids

See all

Distance

- (•) Bird's-eye View
- ( ) Driving (5 mi.)
- ( ) Biking (2 mi.)
- ( ) Walking (1 mi.)
- ( ) Within 4 blocks

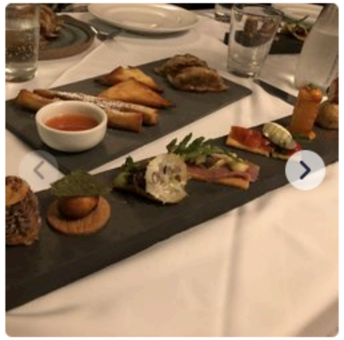
1. A Pão de Queijaria

(31) 2512-6360
R. Antônio de Albuquerque, 856

20

$$ • Cafes

"Our first taste of the touted Minas Gerais pão de queijo had to be at a place that specialized in it. We found this place on Yelp and knew we needed to try out be pão de queijo hamburger. The place itself is cozy, with sidewalk seating and inside open air seating, as well as a small high bar..." more



2. Glouton

(31) 3292-4237
R. Bárbara Heliodora, 59

19

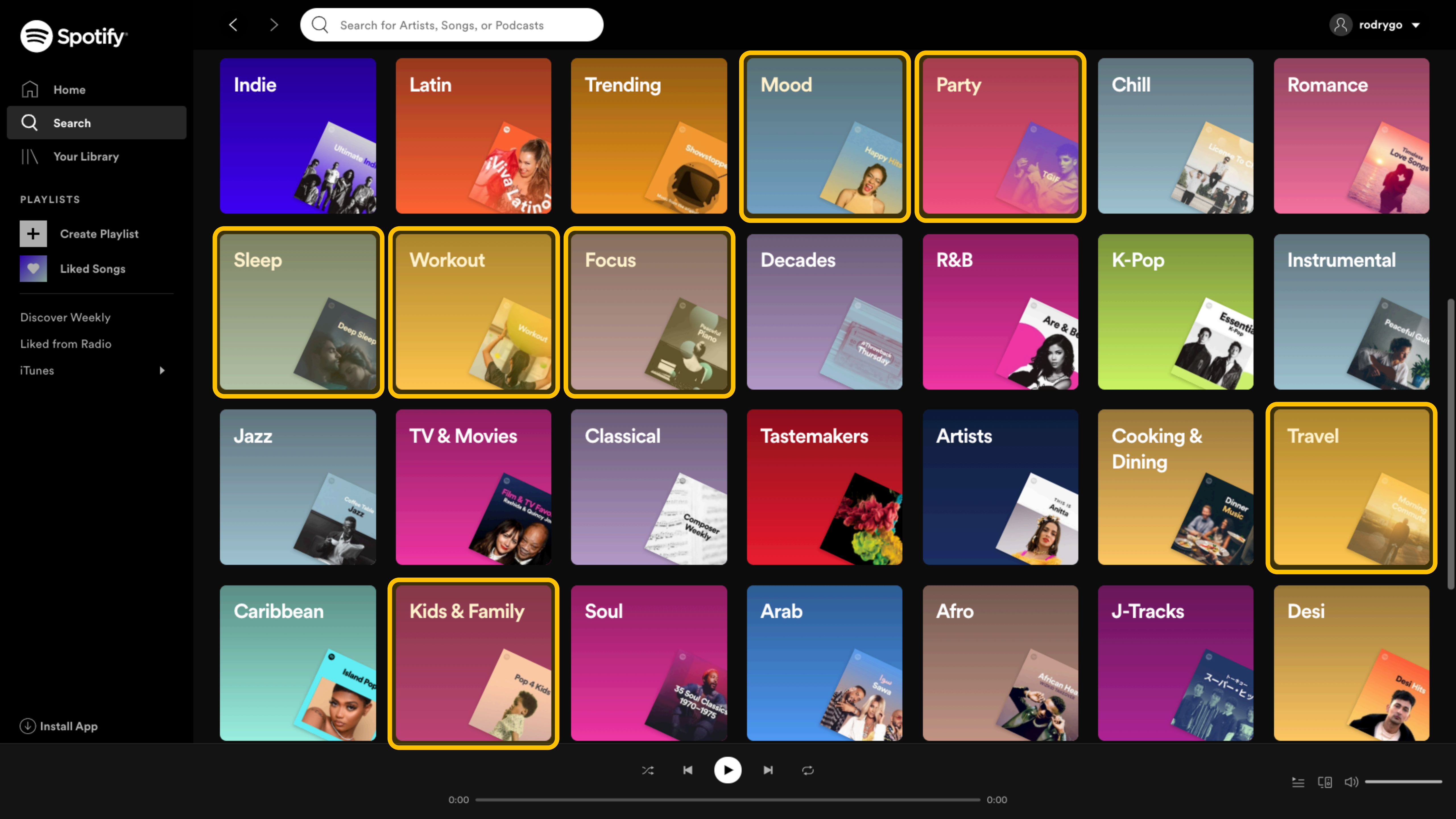
$$$ • French, Brazilian

"Glouton is my favorite restaurant in all of Brazil! My classmates likewise enjoyed the food here so much that we returned to the restaurant multiple times throughout our stay in Belo Horizonte. Rafa was the only server who spoke English, but she always took care of us well. The dishes Glouton serves..." more

3. Restaurante Xapuri

(31) 3496-6198
R. Mandacaru, 260

29


Spotify
Search for Artists, Songs, or Podcasts
rodrygo
Home
Search
Your Library
PLAYLISTS
Create Playlist
Liked Songs
Discover Weekly
Liked from Radio
iTunes
Install App
Indie
Latin
Trending
Mood
Party
Chill
Romance
Sleep
Workout
Focus
Decades
R&B
K-Pop
Instrumental
Jazz
TV & Movies
Classical
Tastemakers
Artists
Cooking & Dining
Travel
Caribbean
Kids & Family
Soul
Arab
Afro
J-Tracks
Desi
0:00
0:00

What is context?

"

Any information that can be used to characterize the situation of entities

- Dey et al., 2001

Everything that affects computation except its explicit input and output

- Lieberman and Selker, 2000

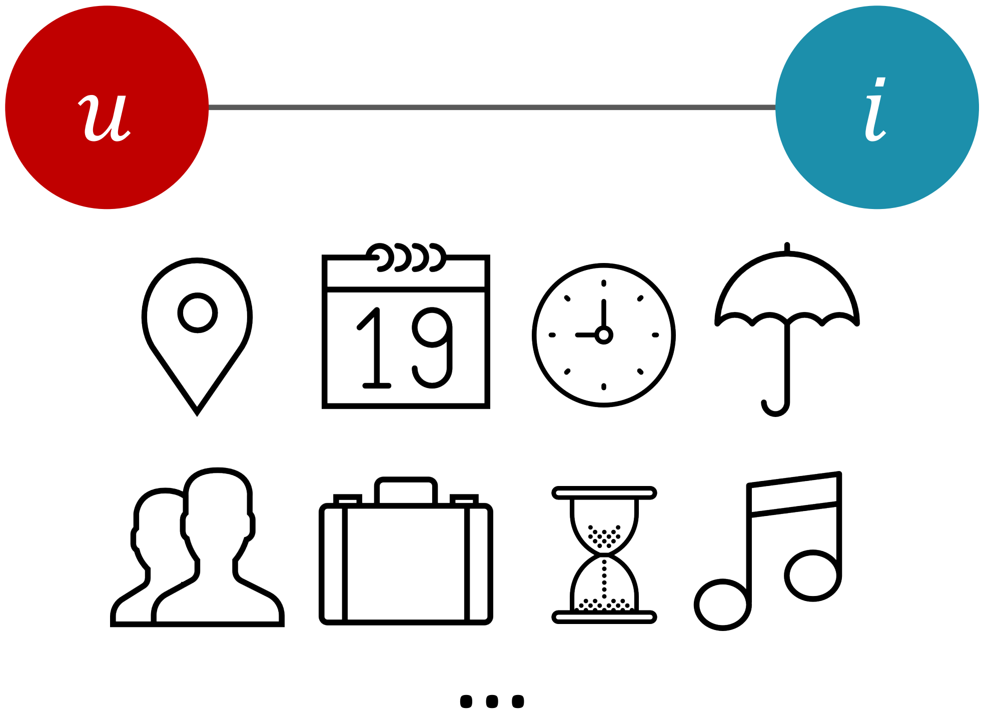
Types of context [Fling, 2009]

Physical: time, position, activity, weather, light, and temperature

Social: the presence and role of other people around the user

Interaction: device and type of media (text, audio, video, etc.)

Modal: state of mind, goals, mood, experience, cognition



Views of context [Dourish, 2004]

Representational view

- Context described using a set of "appropriate" attributes
- Attributes must be observable and distinguishable from the underlying user actions

Representational view: assumptions

Context can be represented explicitly

- Attributes defined based on domain characteristics
  e.g. time, date, location, mood, task, device, etc.
- Contextual variables can have associated structure
  e.g. Sunday < Weekend

Representational view: implications

Contextual variables must be identified a priori

◦ Hard to determine ***which*** context is relevant (aka the *"qualification problem"*)

Contextual variables are static

◦ Hard to determine ***when*** each context is relevant

Collaborative recommendation

	i_1	i_2	i_3	i_4
u_1	4	3	3	
u_2	5			3
u_3		1	2	1

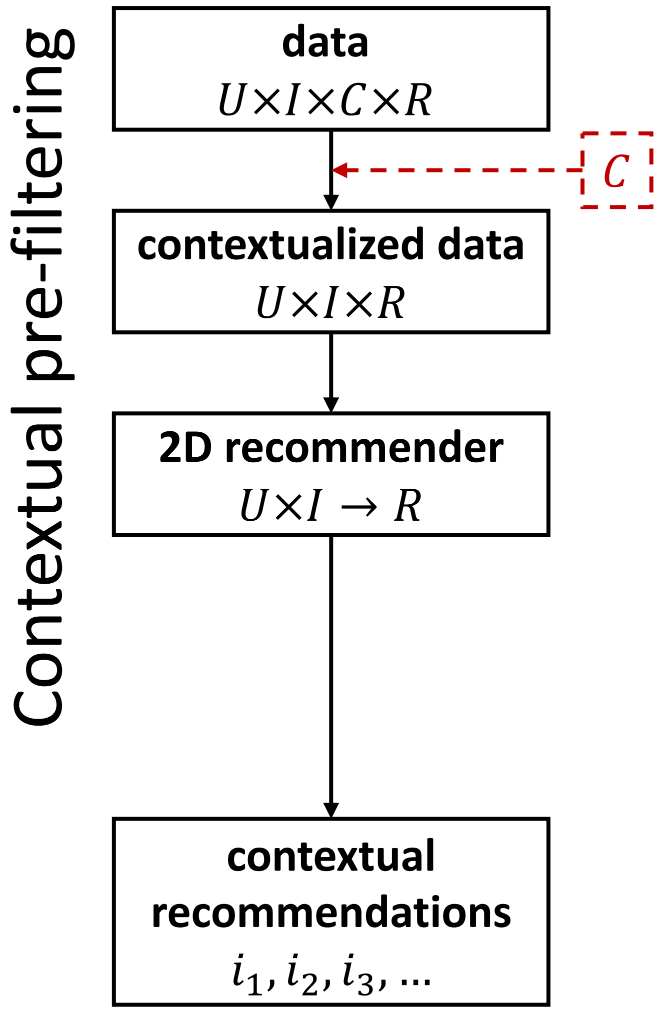
Context-aware recommendation

User	Item	Rating	Time	Location	Companion
u_1	i_1	4	weekend	home	family

Context-aware recommendation

User	Item	Rating	Time	Location	Companion
u_1	i_1	4	weekend	home	family
u_2	i_1	5	weekday	home	family
u_3	i_1	4	weekday	cinema	friend
u_1	i_1	?	weekday	home	friend

Architectures [Adomavicius and Tuzhilin, 2008]



Pre-filtering via splitting

Item splitting

- Preference for an item may change in different contexts
- We may consider the item as multiple items, one for each contextual condition

Example: item splitting

User	Item	Rating	Time	Location	Companion
u_1	i_1	3	weekend	home	spouse
u_1	i_1	5	weekday	cinema	family
u_1	i_1	?	weekday	home	family

Example: item splitting

User	Item	Rating
u_1	i_{1h}	3
u_1	i_{1c}	5
u_1	i_{1h}	?

Pre-filtering via splitting

Item splitting

- Preference for an item may change in different contexts
- We may consider the item as multiple items, one for each contextual condition

User splitting

- User behavior may change in different contexts
- We may consider each user as multiple users, one for each contextual condition

Example: user splitting

User	Item	Rating	Time	Location	Companion
u_1	i_1	3	weekend	home	spouse
u_1	i_1	5	weekday	cinema	family
u_1	i_1	?	weekday	home	family

Example: user splitting

User	Item	Rating
u_{1s}	i_1	3
u_{1f}	i_1	5
u_{1f}	i_1	?

Challenge: splitting criteria

Splitting on certain contexts may be innocuous

- e.g. users rate the same regardless of location

Solution: test whether users (items) rate (are rated) differently given a change in context

- e.g. average rating at home vs. in cinema
- Differences tested for statistical significance

Challenge: context granularity

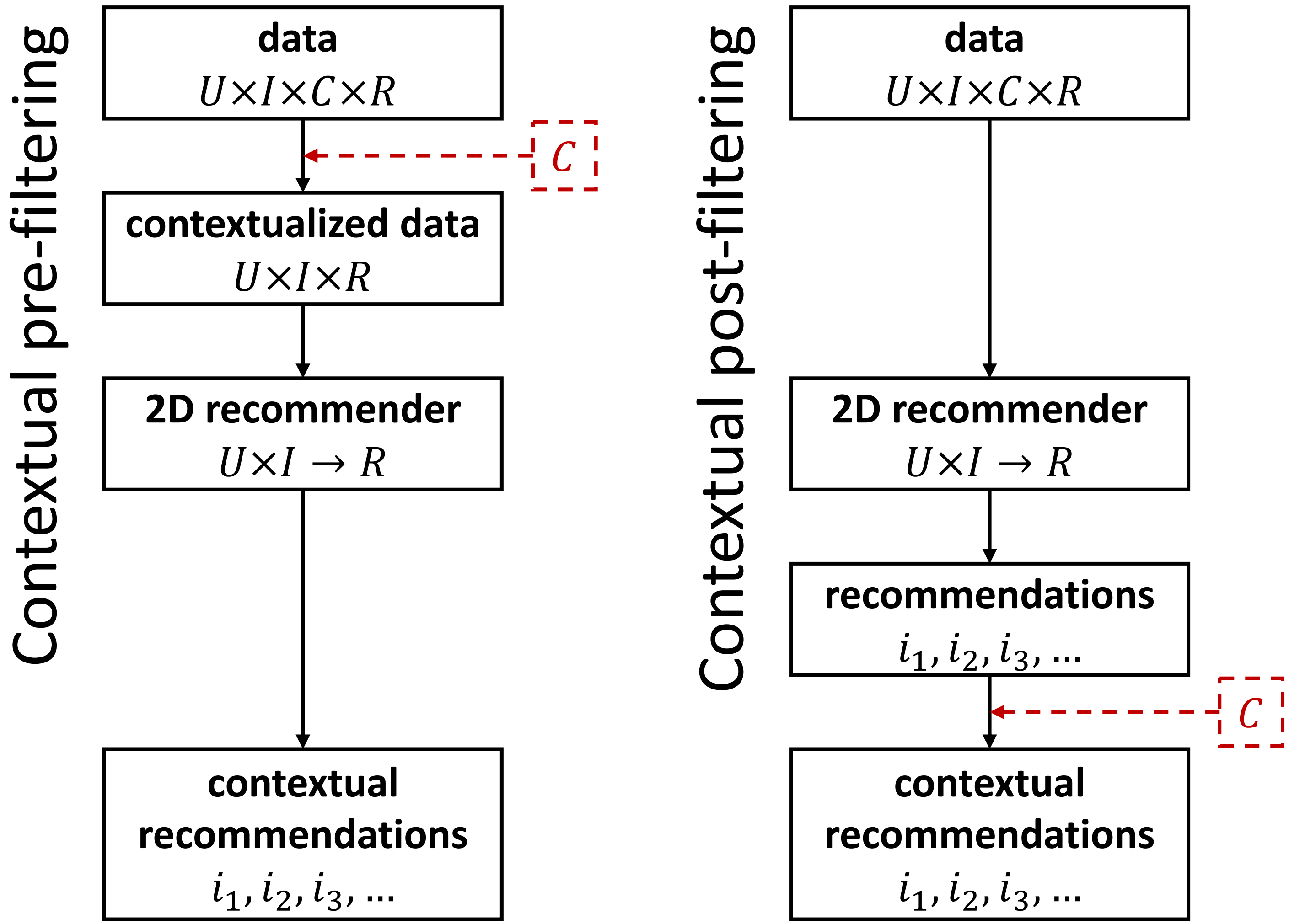
Overly specified contexts may not have enough training examples for accurate prediction

- e.g. movie with girlfriend in <u>cinema</u> on <u>Saturday</u>

Solution: roll-up to higher level contexts

- *cinema* → *anywhere*
- *Saturday* → *weekend*

Architectures [Adomavicius and Tuzhilin, 2008]



Post-filtering based on context similarity

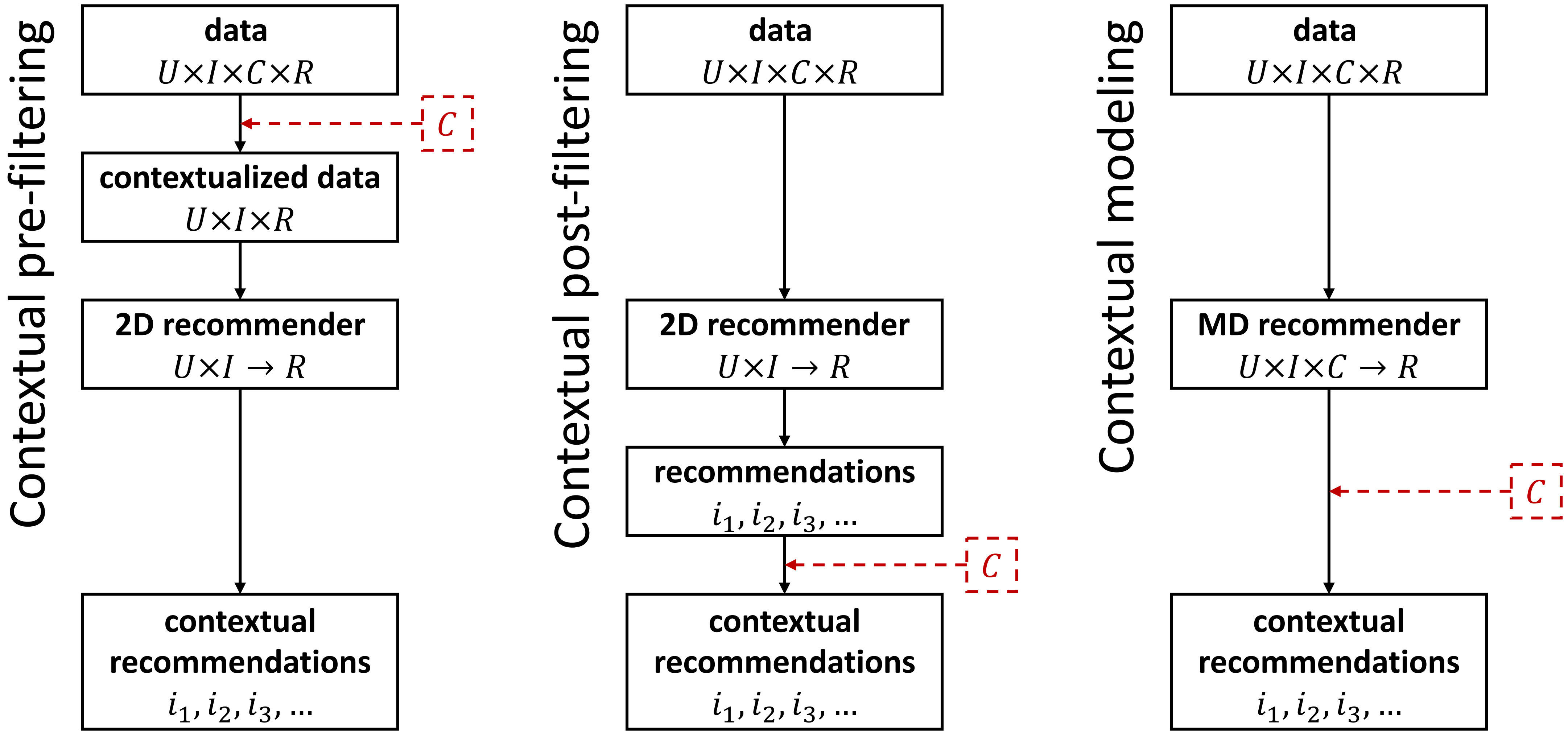
Build context representation

- e.g., annotations, tags, tweets, reviews, etc. associated with items and users in a given context

Re-rank to boost context-awareness

- Promote items similar to the current context

Architectures [Adomavicius and Tuzhilin, 2008]



Contextual modeling via factorization

Recent approaches to contextual modeling attempt to fit the data using various regression models

- Tensor Factorization (TF)
- Factorization Machines (FM)

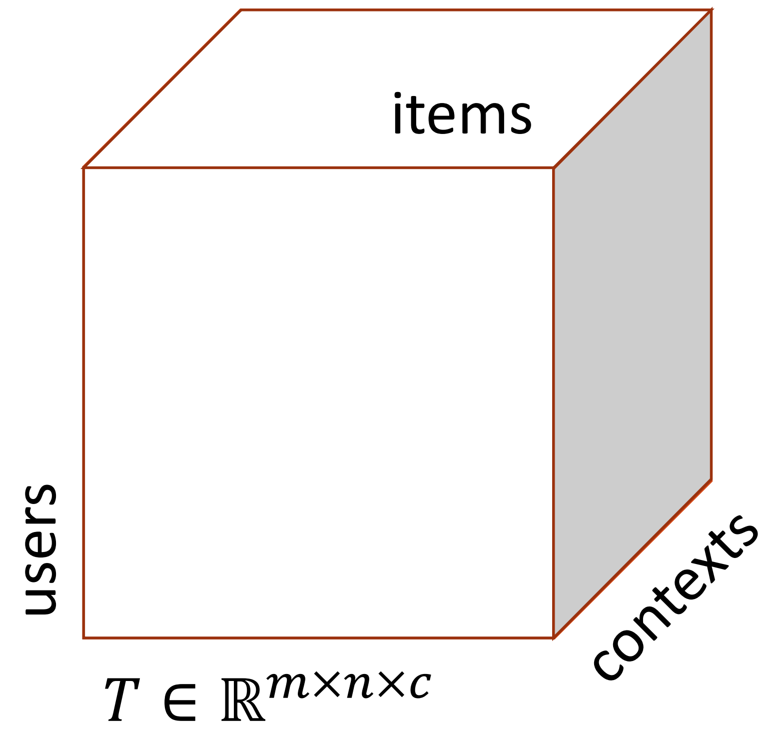
Tensor factorization

Extends two-dimensional matrix factorization into a multi-dimensional version of the same problem

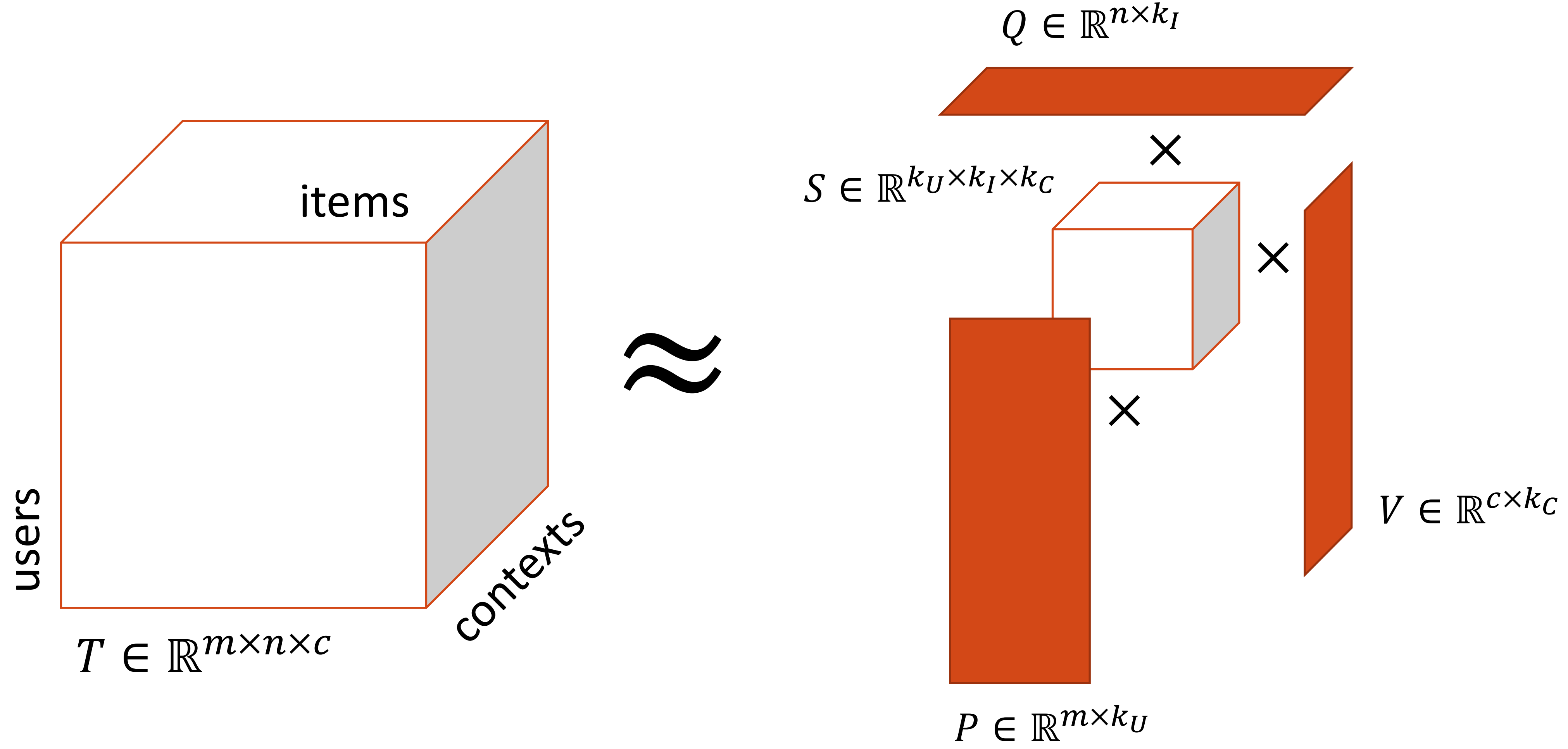
- Multi-dimensional tensor factored into lower-dimensional user, item, and context vectors

Challenge: number of parameters grows exponentially with the number of contextual factors

Tensor factorization



Tensor factorization



Views of context [Dourish, 2004]

Representational view

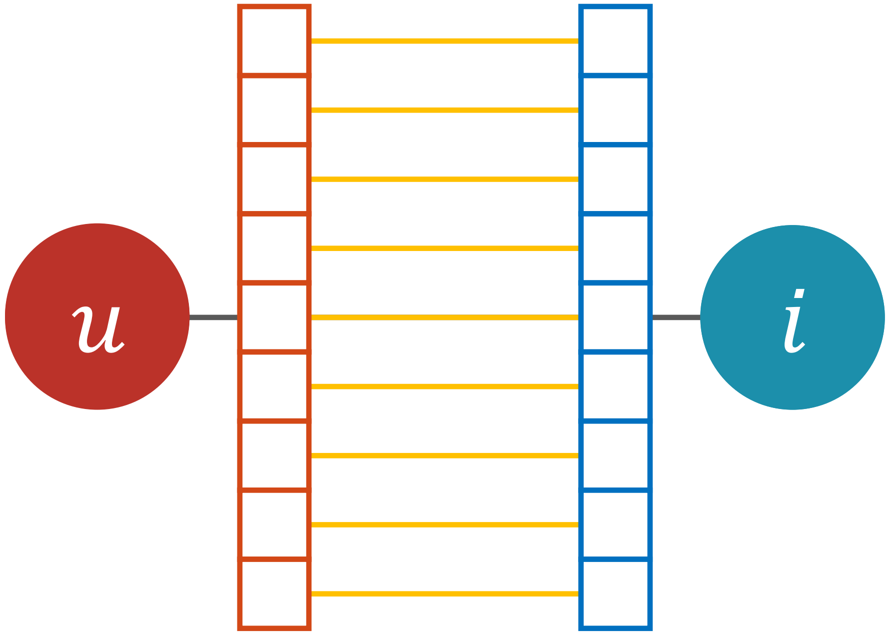
- Context described using a set of "appropriate" attributes
- Attributes must be observable and distinguishable from the underlying user actions

Interactional view

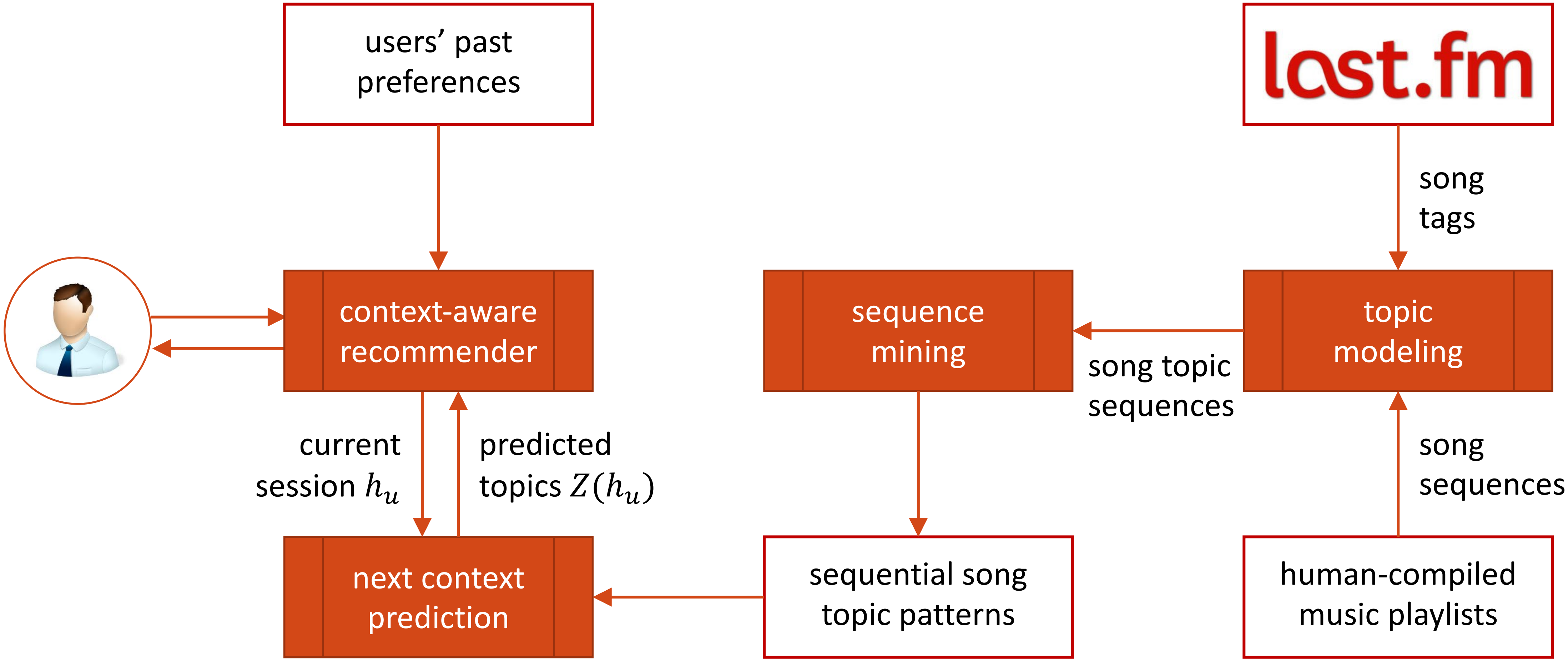
- Context inferred dynamically from user interactions
- Context is latent: context gives rise to user actions, which in turn change the context

Latent variable models

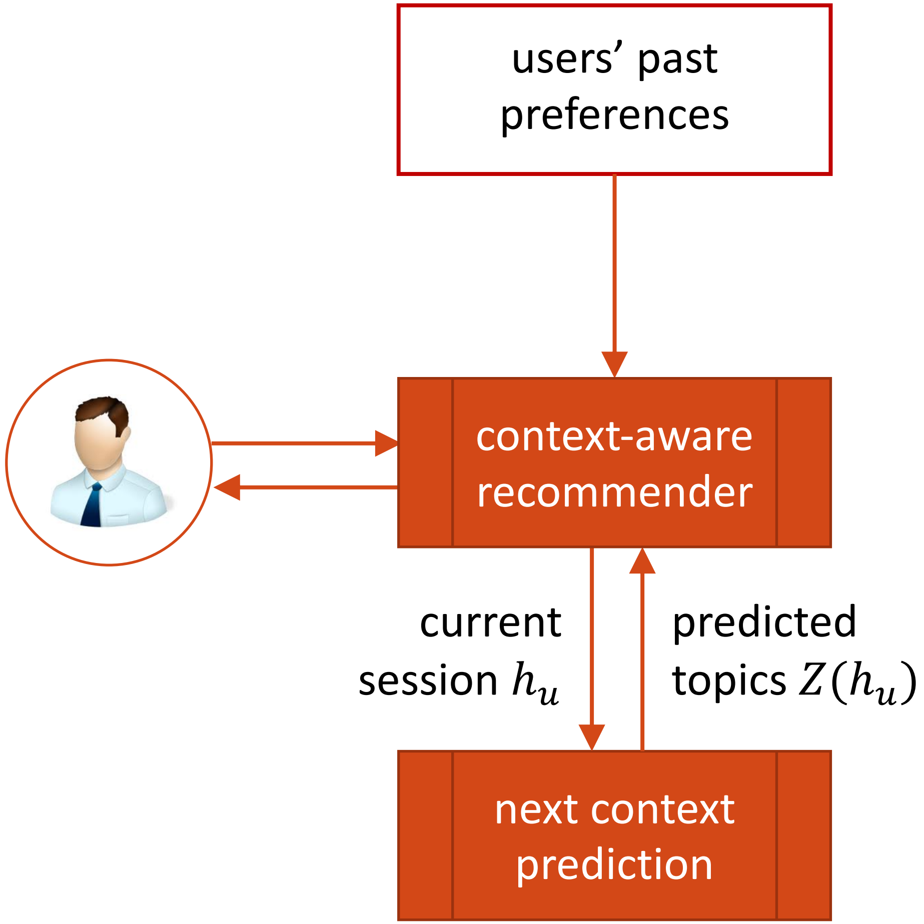
Key assumption: observed interactions can be explained by unobserved contextual variables



Example: topics as context [Hariri et al., 2012]



Example: topics as context [Hariri et al., 2012]



Predicted topics $Z(h_u)$ used to contextualize candidate song i

- $\hat{r}_{ui}^{X} = \frac{1}{|Z(h_u)|} \sum_{z \in Z(h_u)} p(z|i)$

Context score $\hat{r}_{ui}^{X}$ combined with collaborative filtering score $\hat{r}_{ui}^{C}$

- $\hat{r}_{ui} = (\hat{r}_{ui}^{X} + \alpha_1)(\hat{r}_{ui}^{C} + \alpha_2)$

Summary

Context can improve recommendations

- Beyond user-item interactions

Representational models

- Contextual variables engineered as features

Interactional models

- Contextual cues inferred from user interactions

References

The recommender problem revisited
Amatriain and Mobasher, KDD 2014

Recommender Systems Handbook (Ch. 7)

Recommender Systems: The Textbook (Ch. 8)