



UNIVERSITAT DE
BARCELONA



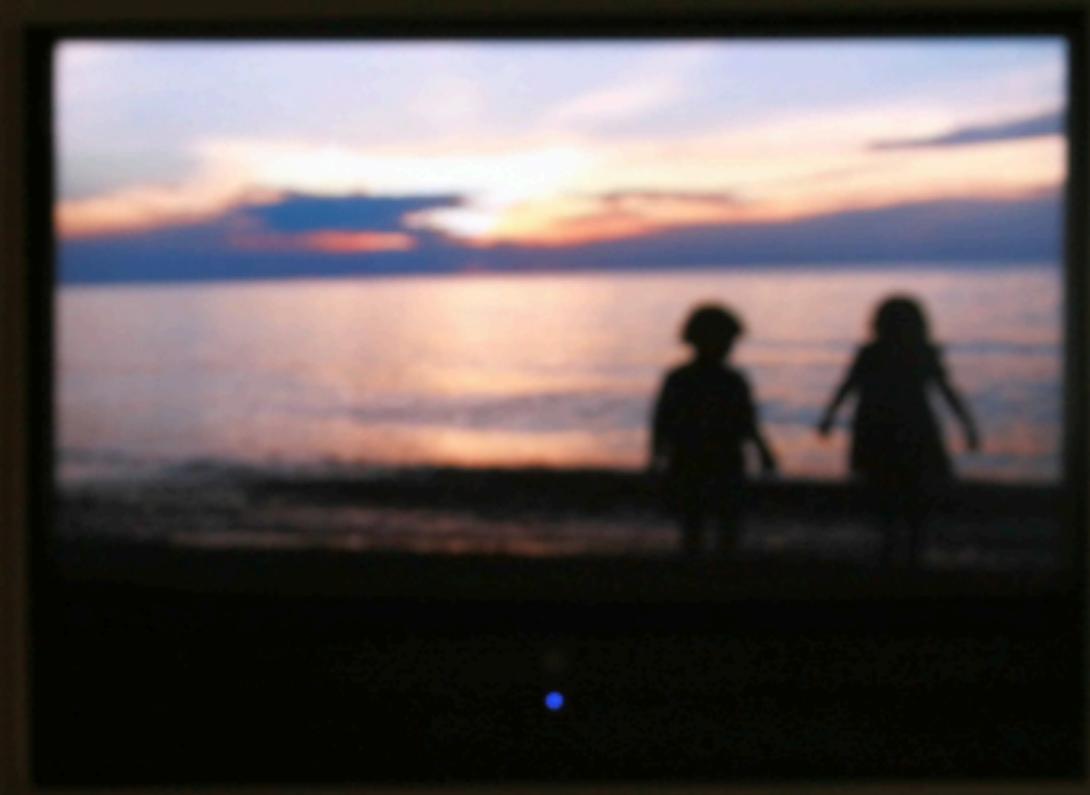
Master on Foundations of Data Science



Recommender Systems

Context Based Recommendations

Santi Seguí | 2018-2019



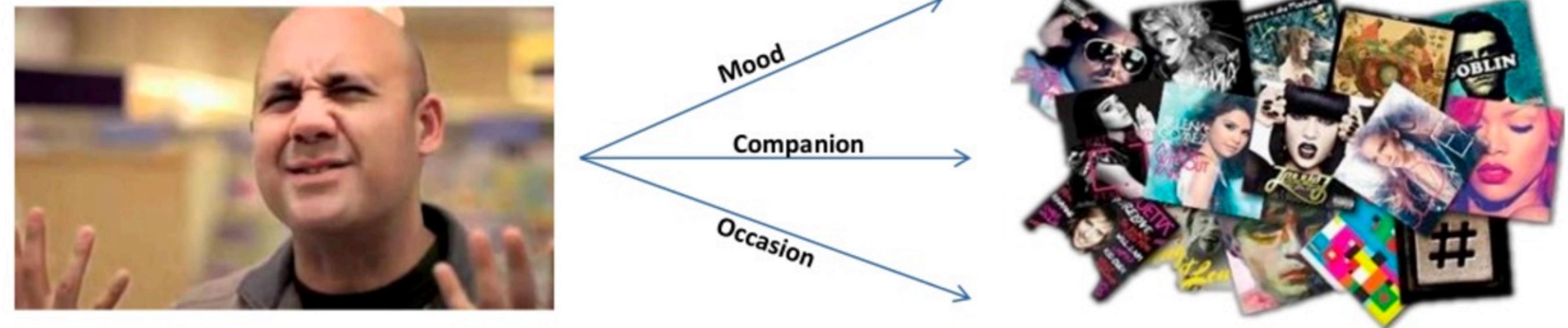


Any movie you prefer to see at **home** than
at the **theater**?

and viceversa?



Non-Context vs. Context



Decision = Rational + Contextual

Context Based Recommenders

- Sensitive to additional information that defines the specific situation under which recommendations are made:
 - **Time:** weekends, holidays, night/day, summer/winter
 - Recommendation that is relevant to the morning context, may not be relevant in the evening and vice-versa.
 - **Location:** A traveling user might wish to determine a recommendation for a restaurant in her location
 - **Social information:** Social context is important. For example, the choice of a user's friends, tags, and social circles can affect the recommendation process

Context Based Recommenders

- Examples:
 - **Travel destination:** in winter vs. summer
 - **Movie watching:** with children vs. with partner
 - **Restaurant:** quick lunch vs. business dinner
 - **Music:** workout vs. study

What is context?

- “**Context** is any information that can be used to characterize the situation of an entity” by Anind K.Dey, 2001

How Contextual Factors Change	Knowledge of the RS about the Contextual Factors		
	Fully Observable	Partially Observable	Unobservable
Static	Everything Known about Context	Partial and Static Context Knowledge	Latent Knowledge of Context
Dynamic	Context Relevance Is Dynamic	Partial and Dynamic Context Knowledge	Nothing Is Known about Context

- Representative context: Fully observable and static
- Interactive Context: Non-f fully observable and Dynamic

Context Dimension

- Explicit:
 - Location, Time, Device, Language,...
- Implicit:
 - Mood, Companion,...

“**Contextual factors** can greatly influence the utility of recommendations for users. In many recommendation and personalization applications, particularly in domains where user context changes dynamically, it is difficult to represent and **model contextual** factors directly, but it is often **possible** to observe their impact on user preferences **during the course of users’ interactions with the system**”

Context adaptation in interactive recommender systems

N Hariri, B Mobasher, R Burke

Proceedings of the 8th ACM Conference on Recommender systems, 41-48

18 2014

Context Acquisition (Real Time)



Context Acquisition (Explicit)

 tripadvisor® Bologna Hotel Pisa

Bologna Hotel Pisa

2,026 Reviews | #6 of 67 Hotels in Pisa

Via Giuseppe Mazzini, 57, 56125, Pisa, Italy | Hotel amenities

Traveler rating	Traveler type	Time of year	Language
<input type="checkbox"/> Excellent 789	<input type="checkbox"/> Families (385)	<input type="checkbox"/> Mar-May (486)	<input checked="" type="radio"/> All languages
<input type="checkbox"/> Very good 865	<input type="checkbox"/> Couples (933)	<input type="checkbox"/> Jun-Aug (580)	<input type="radio"/> English (1,331)
<input type="checkbox"/> Average 258	<input type="checkbox"/> Solo (161)	<input type="checkbox"/> Sep-Nov (512)	<input type="radio"/> Italian (378)
<input type="checkbox"/> Poor 77	<input type="checkbox"/> Business (142)	<input type="checkbox"/> Dec-Feb (448)	<input type="radio"/> Spanish (105)
<input type="checkbox"/> Terrible 37	<input type="checkbox"/> Friends (182)		More

 Yong Zheng

Start your review of Bologna Hotel Pisa (Receive 100 points)

 [Click to rate](#)

Context Acquisition (Explicit)

 tripadvisor® Bologna Hotel Pisa

Your overall rating of this property Draft saved at 10:01 AM.



Title of your review

Summarize your visit or highlight an interesting detail

Your review Tips for writing a great review

Tell people about your experience: your room, location, amenities?

(200 character minimum)

What sort of trip was this?

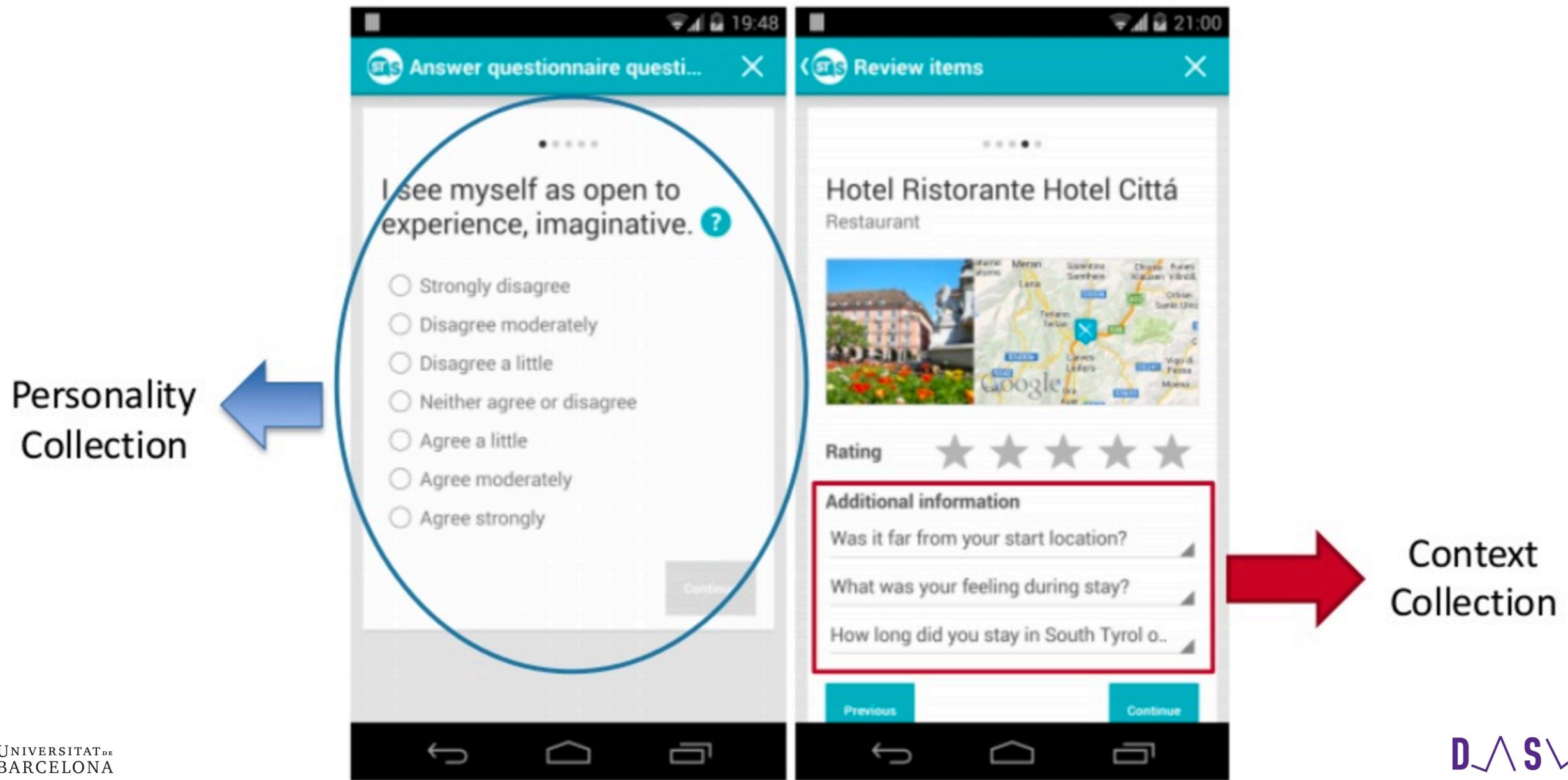
Business Couples Family Friends Solo

When did you travel?

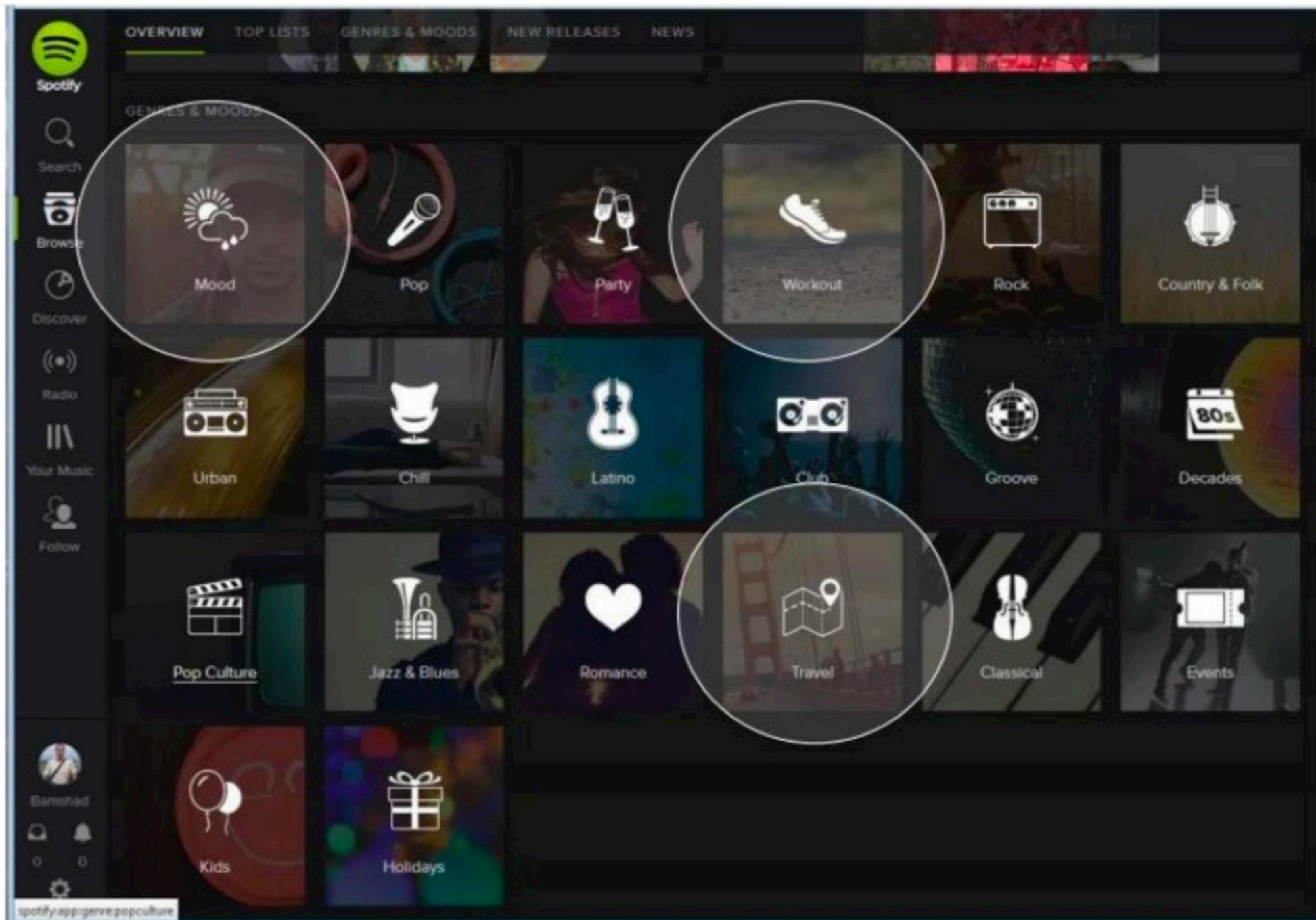
Select one ▾

Context Acquisition (Explicit)

Mobile App: South Tyrol Suggests



Context Acquisition (Predefined)



Context Acquisition (Predefined)

Google Music: Listen Now

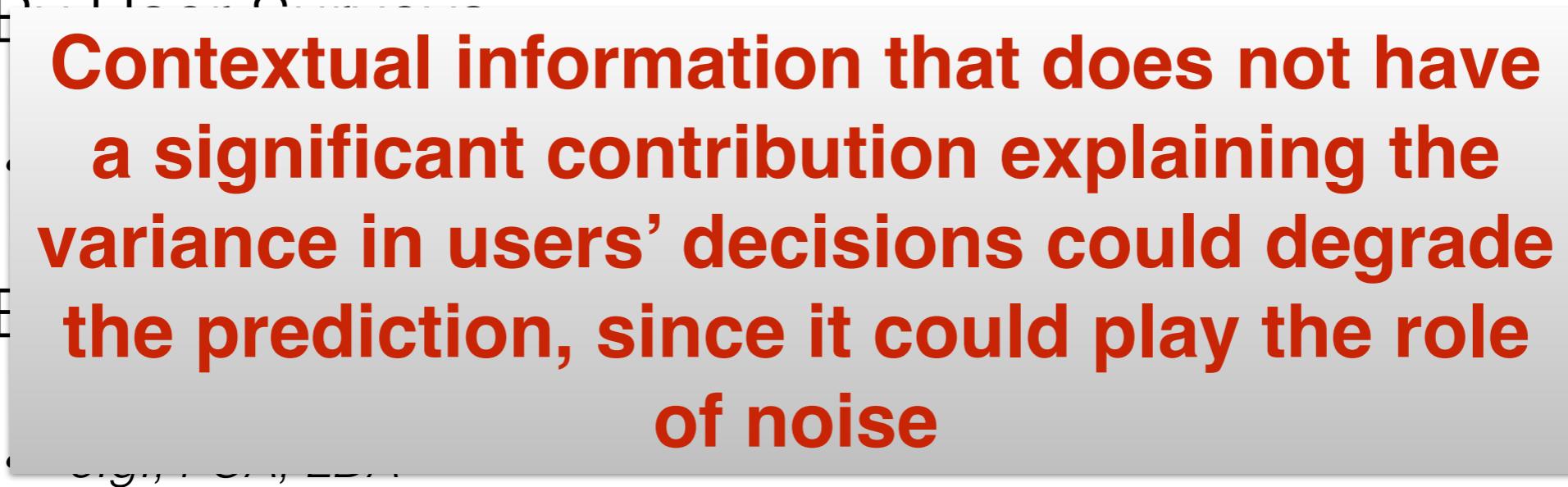
The screenshot shows the Google Music mobile application. At the top, there is an orange header bar with a menu icon (three horizontal lines) and the text "Listen Now". To the right of the menu is a search bar with a magnifying glass icon and the placeholder text "Search music". Below the header, a message says "It's Saturday afternoon" and "Play something for...". There are four large cards, each representing a predefined context:

- Working Out**: Represented by a red square containing a blue dumbbell.
- Cleaning the House**: Represented by a teal square containing a white vacuum cleaner over a blue house.
- Hanging Out**: Represented by a purple square containing a white bowl filled with yellow popcorn.
- Relaxing at Home**: Represented by a light blue square containing a purple armchair.

Context Acquisition

- How to **collect the context** and user preferences in contexts?
 - **By users surveys or explicitly asking for user inputs**
 - **By usage data**
 - The log data usually contains time and locations (at least);
 - User behaviors can also infer context signals;
 - Cross domain applications

Which context is important?

- Not all of the context are relevant or influential. How can we find the importance of the context?
-  **Contextual information that does not have a significant contribution explaining the variance in users' decisions could degrade the prediction, since it could play the role of noise**
- By Statistical Analysis or Detection on Contextual Ratings
 - *Statistical test, Mutual Information, Information Gain*

Context for Movie Recommender System

Which is the important contextual information?

How can we estimate it?

Relevant context in a movie recommender system: Users' opinion vs.
statistical detection

A Odic, M Tkalcic, JF Tasic, A Košir
ACM RecSys 12

40 2012

Context for **Movie** Recommender System

Context for **Trivago** Recommender System

Context for Movie Recommender System

Contextual variable	Description
time	morning, afternoon, evening, night
daytype	working day, weekend, holiday
season	spring, summer, autumn, winter
location	home, public place, friend's house
weather	sunny/clear, rainy, stormy, snowy, cloudy
social	alone, partner, friends, colleagues, parents, public, family
endEmo	sad, happy, scared, surprised, angry, disgusted, neutral
dominantEmo	sad, happy, scared, surprised, angry, disgusted, neutral
mood	positive, neutral, negative
physical	healthy, ill
decision	user picked the item, item suggested by other
interaction	first, n-th

Relevant context in a movie recommender system: Users' opinion vs. statistical detection

A Odic, M Tkalcic, JF Tasic, A Košir
ACM RecSys 12

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Context for Movie Recommender System

how do we obtain the data?

- via user-survey
- via the detection from the rating data

Relevant context in a movie recommender system: Users' opinion vs.
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40 2012

Context for Movie Recommender System

Table 3: Assessment and detection results.

Assessment		Detection	
Relevant	Irrelevant	Relevant	Irrelevant
time		daytype	
location	day type	location	time
social	season	endEmo	season
endEmo	weather	domEmo	weather
domEmo	physical	mood	social
mood	decision	physical	
interaction		decision	
		interaction	

How to make a Context Aware Recommender Systems?

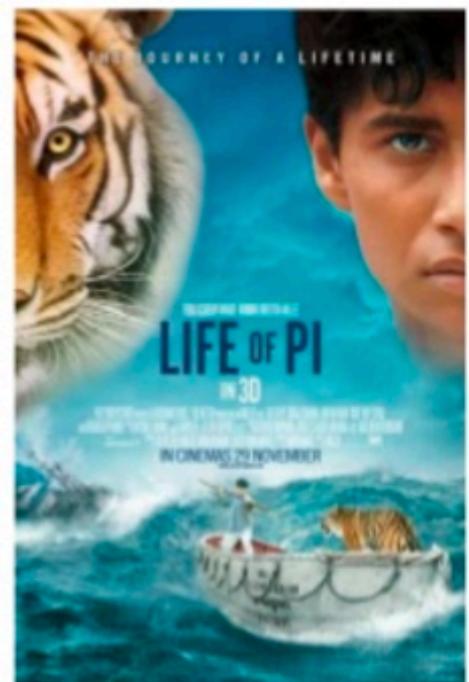
Context-aware RecSys

- **Traditional RS:** Users x Items -> Ratings
- **Contextual RS:** Users x Items x Contexts -> Ratings

User	Item	Rating	Time	Location	Companion
U1	T1	3	Weekend	Home	Kids
U1	T2	5	Weekday	Home	Partner
U2	T2	2	Weekend	Cinema	Partner
U2	T3	3	Weekday	Cinema	Family
U1	T3	?	Weekend	Cinema	Kids

Example of Multi-dimensional Context-aware Data set

Items at different context



At Cinema



At Home



At Swimming Pool



Item Splitting

User	Item	Location	Rating	
U1	M1	Pool	5	High Rating
U2	M1	Pool	5	
U3	M1	Pool	5	
U1	M1	Home	2	Low Rating
U4	M1	Home	3	
U2	M1	Cinema	2	

Significant difference?
Let's split it !!!

Same movie,
different IDs.



M1



M11: being seen at Pool



M12: being seen at Home

Item Splitting

User	Item	Loc	Rating
U1	M1	Pool	5
U2	M1	Pool	5
U3	M1	Pool	5
U1	M1	Home	2
U4	M1	Home	3
U2	M1	Cinema	2

Transformation



User	Item	Rating
U1	M11	5
U2	M11	5
U3	M11	5
U1	M12	2
U4	M12	3
U2	M12	2

Question:

How to find such a split? Pool and Non-pool, or Home and Non-home?
Which one is the best or optimal split?

Item Splitting

- **Splitting Criteria** (Impurity Criteria)
 - Impurity criteria and significance test are used to make the selection
 - Several measures:
 - t_{mean} (t-test), t_{prop} (z-test), t_{χ} (chi-square test), t_{ig} (Information gain)

User Splitting and UI Splitting

- Similarly, the splitting approach can be applied to users too!
 - **User Splitting:** Instead of splitting items, it may be useful to consider one user as two different users, if user demonstrates different preferences across context.
 - **UI Splitting:** simply a combination of item splitting and user splitting - both approaches are applied to create a new rating matrix - new users and new items are created in the rating matrix.

Splitting and Transformation

User	Item	Rating	Time	Location	Companion
U1	T1	3	Weekend	Home	Friend
U1	T1	5	Weekend	Cinema	Girlfriend
U1	T1	?	Weekday	Home	Family



(a) by Item Splitting

User	Item	Rating
U1	T11	3
U1	T12	5
U1	T11	?

(b) by User Splitting

User	Item	Rating
U12	T1	3
U12	T1	5

(c) by UI Splitting

User	Item	Rating
U12	T11	3
U12	T12	5
U11	T11	?

How splitting approaches work?

1. Find the best split to perform a splitting approach
2. After, splitting, we obtain the User-item rating matrix
3. Apply any traditional Recommender Algorithm

Context-Aware Splitting Approaches

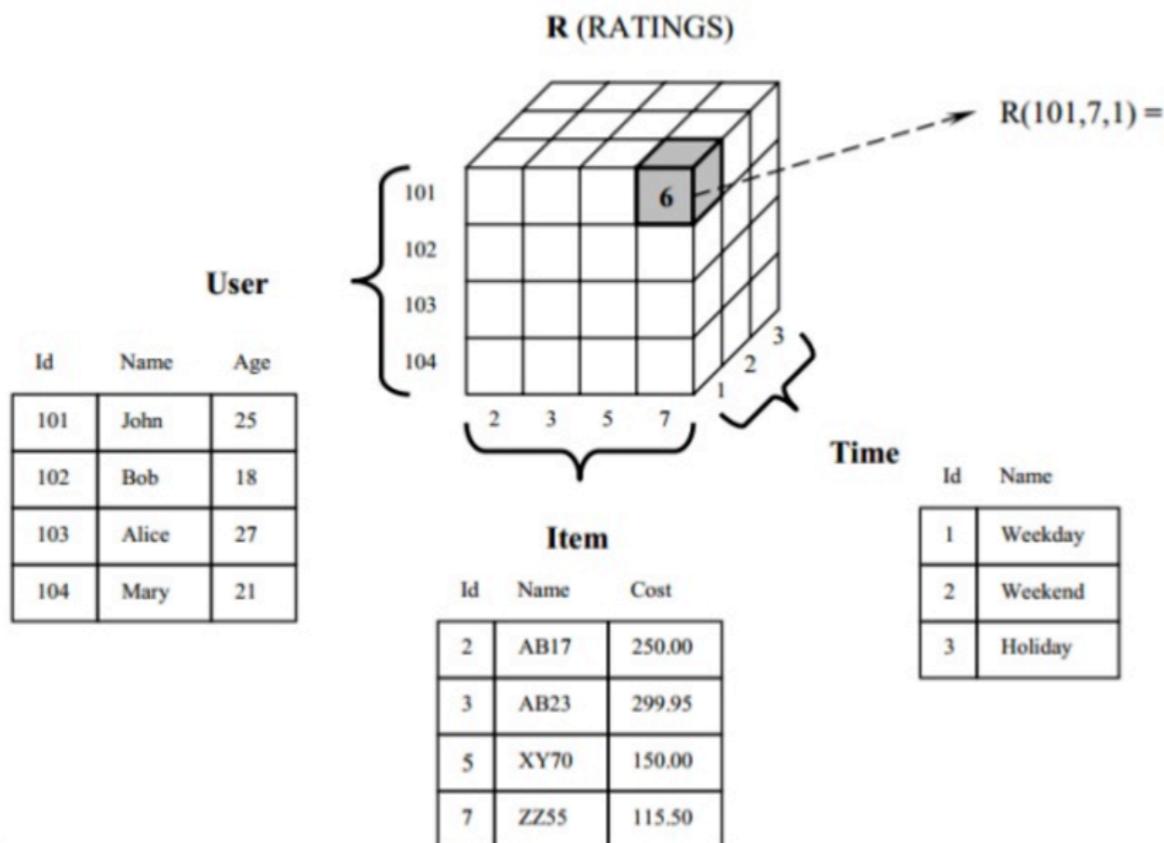
- **Summary:**
 - Pros: Context are fused into user and/or item dimensions
 - Cons: We create new user/items, which increase the sparsity
- **A solution/suggestion:**
 - Create a hybrid recommender to alleviate the data sparsity or cold-start problem introduced by UI Splitting

Contextual Modeling

Independent Contextual Modeling

- Tensor Factorization

Multi-dimensional space: $User \times Items \times Contexts \rightarrow Ratings$

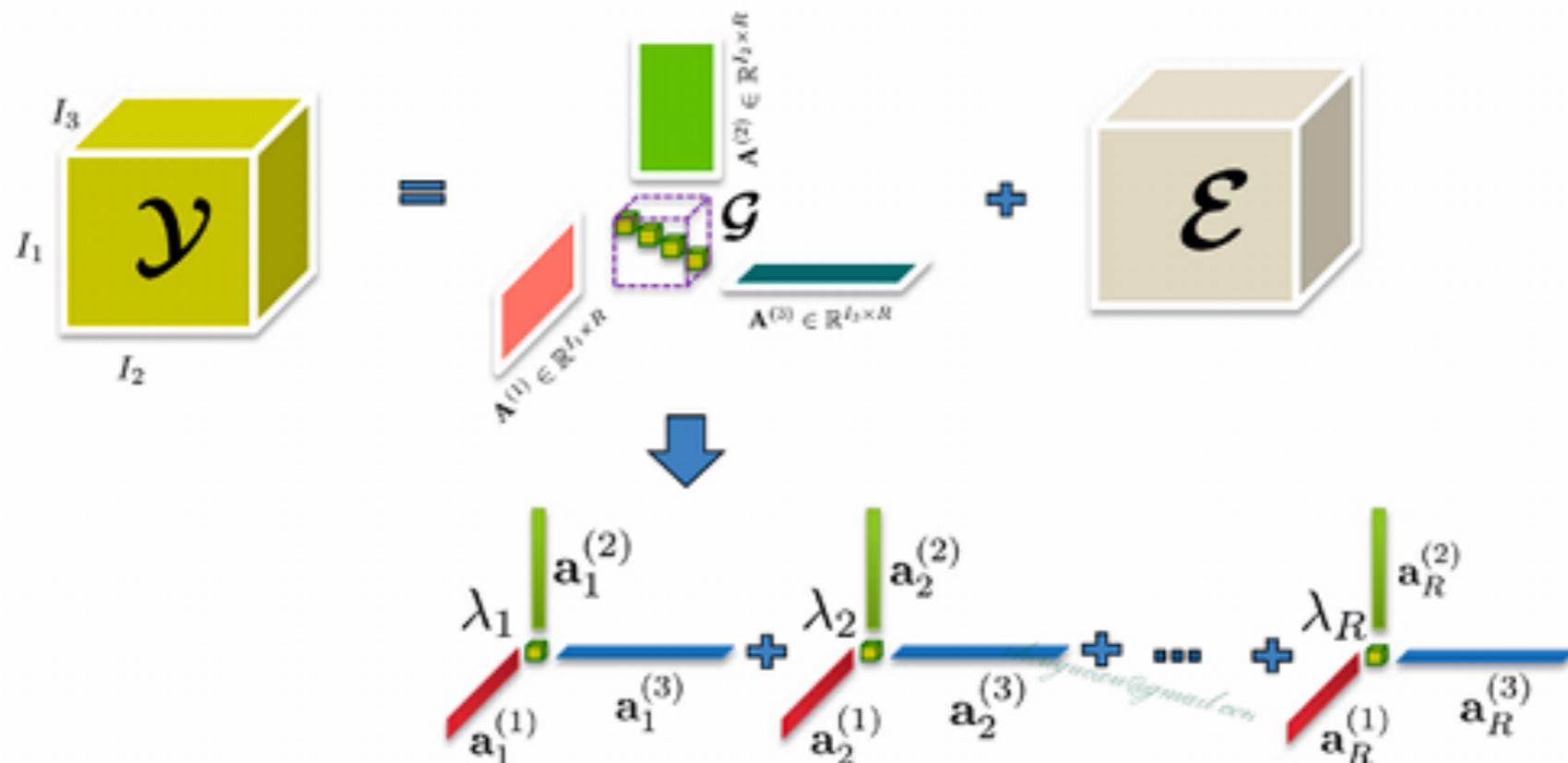


Each context variable is modeled as an individual and independent dimension in addition to user and item dims

Thus we can create a multidimensional space, where rating is the value in the space

Independent Contextual Modeling

By CANDECOMP/PARAFAC Decomposition

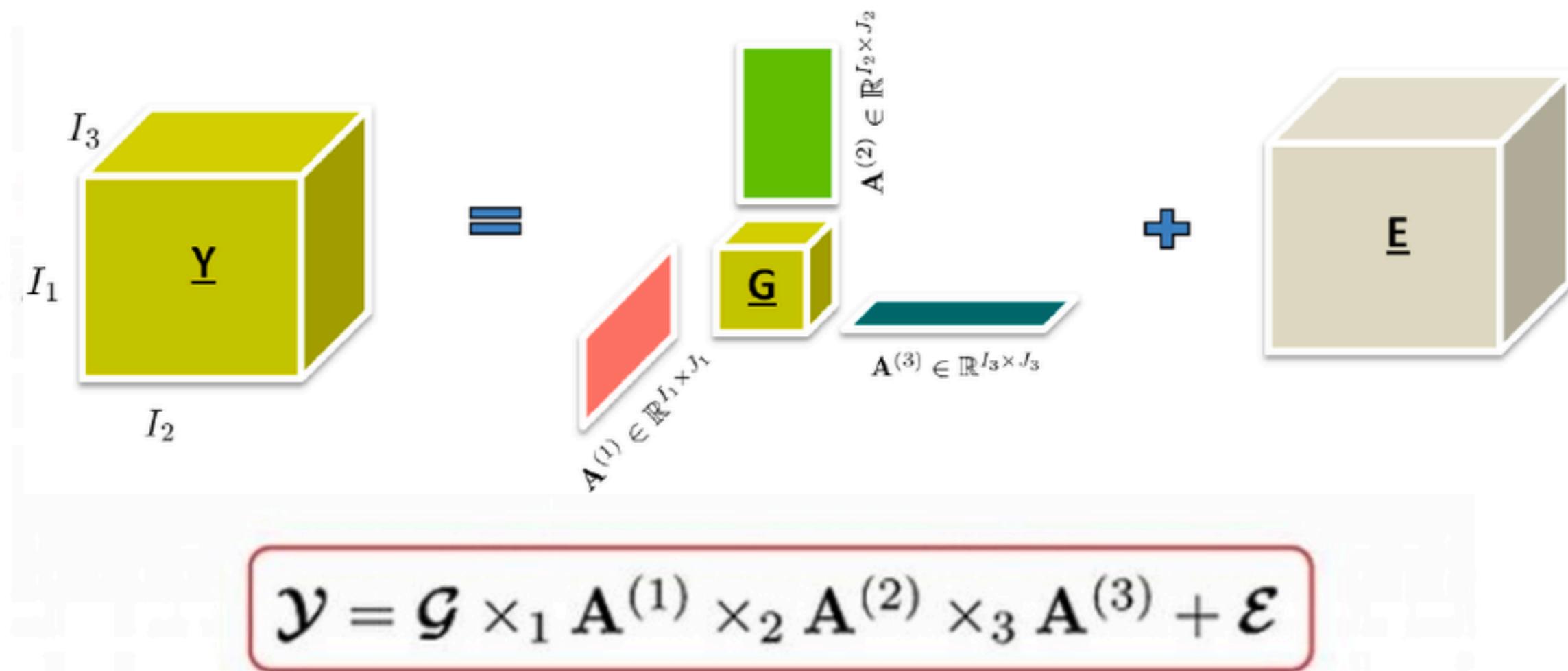


- $R_1 = R_2 = R_3 = R$.
- \mathcal{G} is super diagonal.

$$\mathcal{Y} = \sum_r \lambda_r \mathbf{a}_r^{(1)} \circ \mathbf{a}_r^{(2)} \circ \mathbf{a}_r^{(3)} + \epsilon$$

Independent Contextual Modeling

By Tucker Decomposition: Generalization of the SVD. Decompose a tensor into a core tensor, multiplied by a matrix along each mode



Independent Contextual Modeling

- Tensor Factorization:
 - **Pros:** Straightforward, easily to incorporate contexts into the model
 - **Cons:**
 - 1) Ignore the dependence between contexts and user/items dims
 - 2) Increased computational cost if more context dimensions

Dependent Contextual Modeling

- **Dependence between Users/Items and Contexts**

- Users and Context, such as user splitting
- Item and Context, such as item splitting

For example if a user can be splitted by time (weekend or not) it tells this user is dependent with this context.

- **Dependence between every two contexts**

- Deviation-Based: rating deviation between two contexts
- Similarity-Based: similarity of rating behaviors in two contexts

Deviation-Based Contextual Modeling

- Contextual Rating Deviation (CRD)
 - How user's ratings is deviated from context c1 to c2?

Context	D1: Time	D2: Location
c1	Weekend	Home
c2	Weekday	Cinema
CRD(Di)	0.5	-0.1

- $\text{CRD}(D1) = 0.5 \rightarrow$ Users' rating in Weekday is generally higher than users' rating and Weekend by 0.5
- $\text{CRD}(D2) = -0.1 \rightarrow$ Users' rating in Cinema is generally lower than users' rating at home by 0.1

Deviation-Based Contextual Modeling

- Contextual Rating Deviation (CRD)
 - How user's ratings is deviated from context c1 to c2?

Context	D1: Time	D2: Location
c1	Weekend	Home
c2	Weekday	Cinema
CRD(Di)	0.5	-0.1

- Assume Rating(U, I, c1) = 4
- Predicted Rating (U, T, c2) = Rating(U, I , c1) + CRDs =
$$= 4 + 0.5 - 0.1 = 4.4$$

Deviation-Based Contextual Modeling

- Build a deviation-based contextual modeling approach
 - Assume \emptyset is a special situation: without considering context

Context	D1: Time	D2: Location
\emptyset	UnKnown	UnKnown
c2	Weekday	Cinema
CRD(Di)	0.5	-0.1

- Assume $\text{Rating}(U, I, \emptyset) = \text{Rating}(U, I) = 4$
- Predicted Rating $(U, T, c2) = 4 + 0.5 - 0.1 = 4.4$

$$F(U, I, C) = P(U, I) + \sum_{i=0}^N CRD(i)$$

Deviation-Based Contextual Modeling

- Build a deviation-based contextual modeling approaches:

- Simplest method:

$$F(U, I, C) = P(U, I) + \sum_{i=0}^N CRD(i)$$

- User-personalized model:

$$F(U, I, C) = P(U, I) + \sum_{i=0}^N CRD(i, U)$$

- Item-personalized model:

$$F(U, I, C) = P(U, I) + \sum_{i=0}^N CRD(i, I)$$