Context-aware
RECOMMENDER SYSTEMS

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Outline

- What is context?
- Types
- Modelling
  - CA matrix factorisation
- Applications

- *“The ideal context-aware recommendation system would[…] be able to* ***reliably label each user action*** *with an* ***appropriate context*** *and effectively tailor the* ***system output*** *to the user in that* ***given context****.”*

Adomavicius (2011)

What is context in RS?

- Context
  - *"any information useful to characterize the situation of an entity (e.g., a user or an item) that can affect the way users interact with systems"* (Abowd et al., 1999)
- Set of **factors**
  - that delineate **conditions** under which user-item pair is assigned a rating
- **Reasoning**
  - **user preferences for items are not only a function of items themselves, but also a function of the context in which they are considered**
    - preferences for items may be different from one context to another

Context **types**

- *Observed when the recommendation (application) is to be used*

Physical context

Social context

Interaction media context

Modal context

- Alternative classification by Villegas et al. (2018)

Context **types**

- *Observed when the recommendation (application) is to be used*

Physical context

- time, position, user's activity
- weather, light, temperature

Social context

- presence and role of other people around
- is user alone or in a group

Interaction media context

- device used to access application
- type of media viewed/browsed (just text, or also videos, images, etc.)

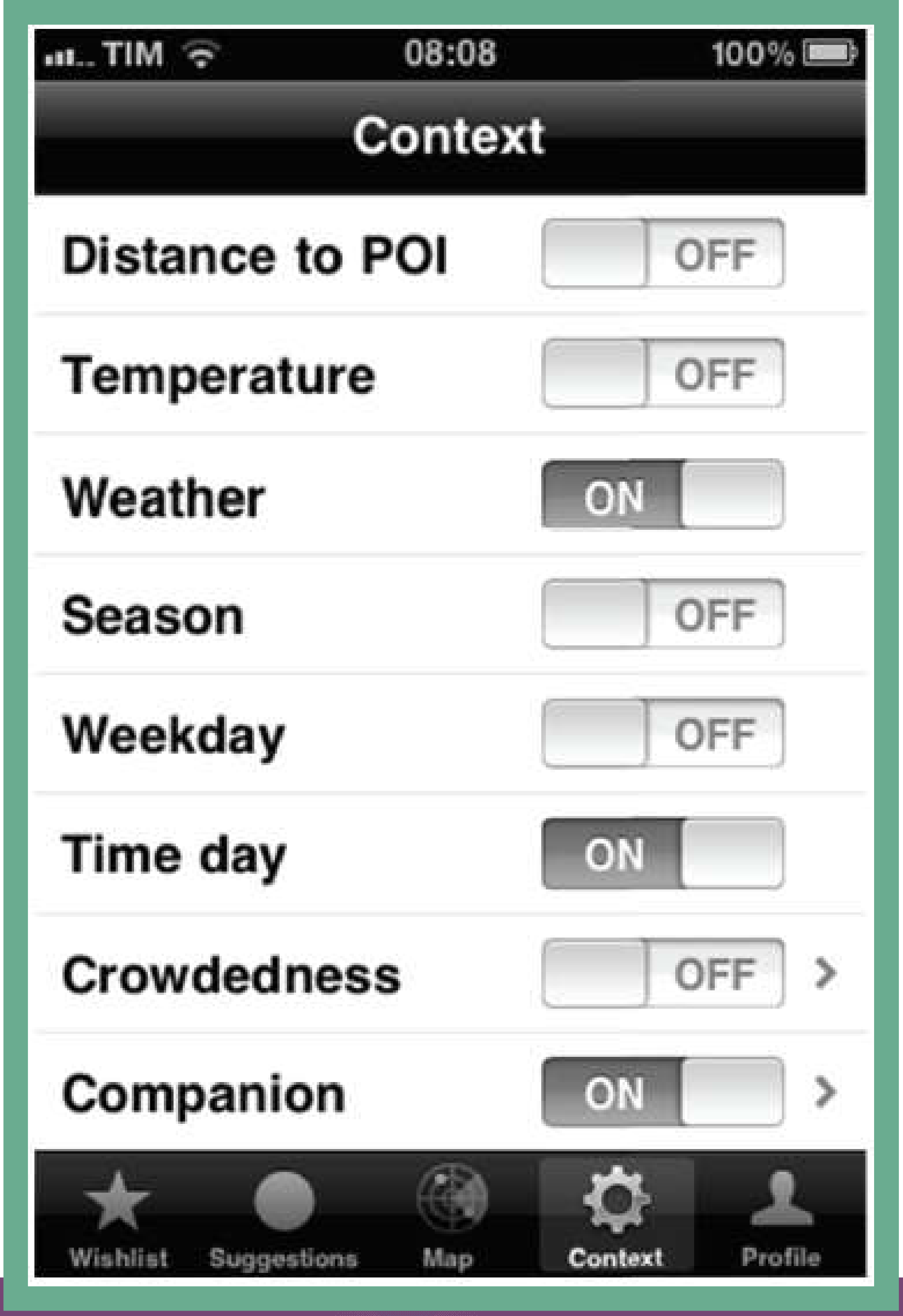
Modal context

- user's current state of mind
  - goals, experience, purpose of visit
  - mood, cognitive capabilities

Source: Adomavicius (2011)

Contextual **data**

- Explicit
  - Explicitly entered/specified by users
- Implicit
  - inferring contextual information
    - building predictive models from historical data



Source: Adomavicius (2011)

Context / factor **structure**

1. **What** does an RS know about contextual factors
   - Fully observable
   - Partially observable
   - Unobservable
2. **How** do contextual factors **change over time**
   - Static
   - Dynamic

- **Intermediate cases**
  - E.g. static unobservable contextual information
    - latent structure stable
    - modelled with latent variables
    - unobserved contextual information learned with
      - e.g., matrix factorisation, probabilistic latent semantic analysis, hierarchical linear models.

Source: Adomavicius (2011)

Contextual situation

- E.g. restaurant recommender
  - System determines user is on -> **romantic date**
    - Hence, **filter out** restaurants that are
      - Noisy
      - Without adequate drink selection
      - …

Task 1: Contextual situation

- Identify a contextual situation for:
  - Music CARS
  - Travel CARS

Modelling context

- Traditional problem
  - **2D** rating function
    - *R : Users x Items -> Ratings*
  - **prediction** problem
    - *what would be the user's rating given a user profile and a target (new / unseen) item?*

- CARS problem
  - **Multidimensional rating function**
    - incorporate additional information
    - ***R : Users x Items x Contexts -> Ratings***
  - Predict / estimate
    - user preferences on unseen items

Modelling context: Prediction

- Predict $\boldsymbol{r_{uic}}$
  - rating for i given by u in c contextual situation
    - c defined by values of contextual factors

$$\boxed{\hat{r}_{uic_1\ldots c_k} = q_i^T p_u + \mu + b_u + \sum_{j=1}^{k} B_{ijc_j}}$$

- Rating $r_{uic1\ldots ck}$
  - user u's rating for item i made in context $c_1, \ldots, c_k$
  - $c_j = 0, 1, \ldots, z_j$ - values / conditions of contextual factor
- Data set $R = \{(u, i, c_1, \ldots, c_k) \mid r_{uic1\ldots ck}$ is known$\}$

ID	Music name and player/singer	Playing time	Playing device	Rating
m_1^u	Hero-Mariah Carey	2016/09/23 19:52	iPod	3
m_2^u	Without You-Mariah Carey	2016/09/23 19:56	iPod	4
m_7^u	Numb-Linkin Park	2016/09/24 15:22	PC	2
m_8^u	Don't Cry-Guns N' Roses	2016/09/24 15:27	PC	4

Modelling context: **Techniques**

- CARS process categorised into:

Contextual **pre-filtering**

- focus of earlier research
- **CACF**
- CARS **content-based**
- CARS with **hybrid** tech.

Contextual **post-filtering**

- CARS with **user-based CF**

Contextual **modelling**

- more recent research
- CARS with **CF**
  - tensor factorisation
- CARS with **hybrid** tech

General rule

- small dataset -> use simpler model

Source: Adomavicius(2011), Baltrunas (2011), Villegas (2018)

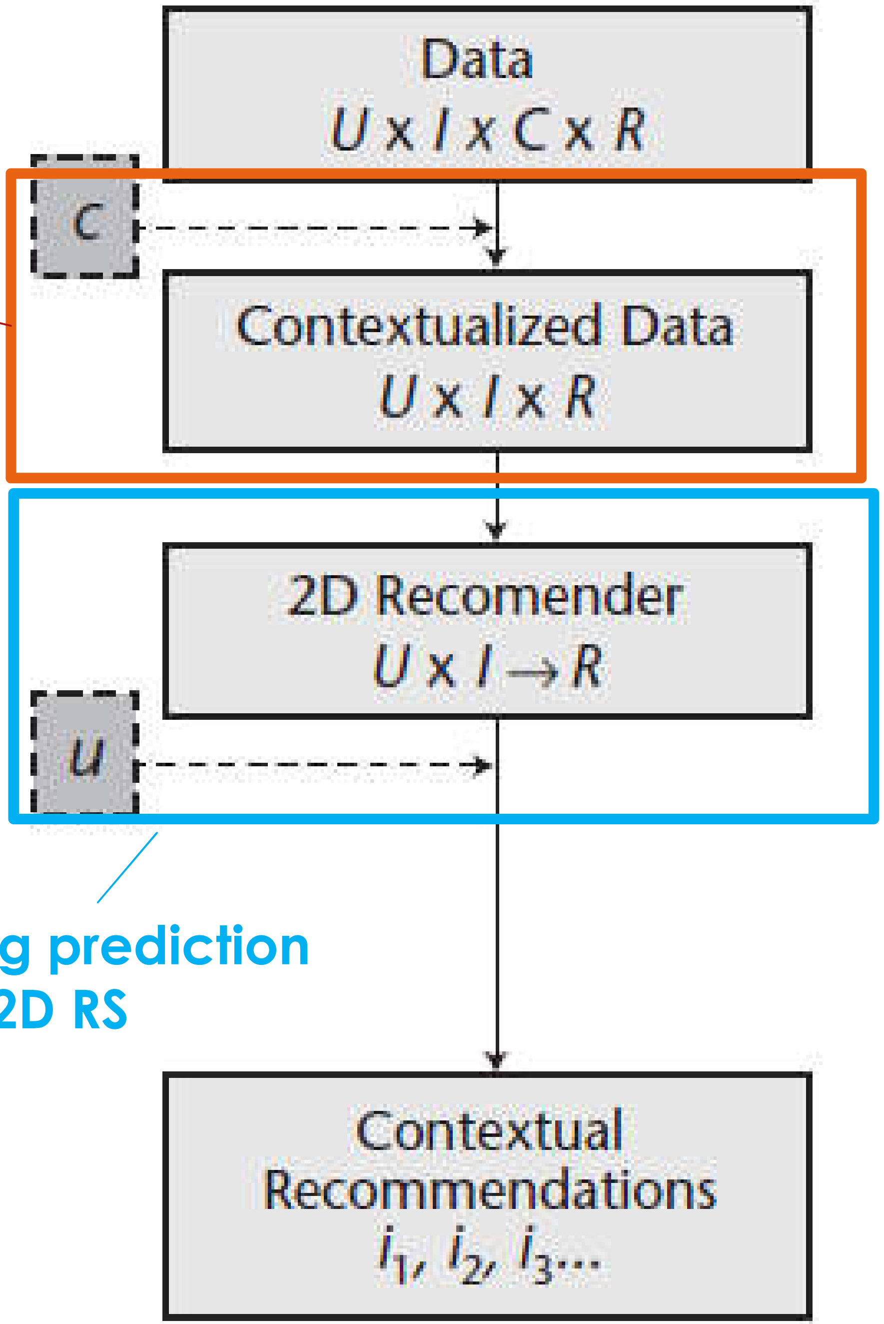
Contextual pre-filtering

Data filtered based on current context c

- Advantage
  - allows deployment of any traditional technique
- Disadvantage
  - overly specific context(s)
    - may not be significant
    - may lack data for accurate rating prediction

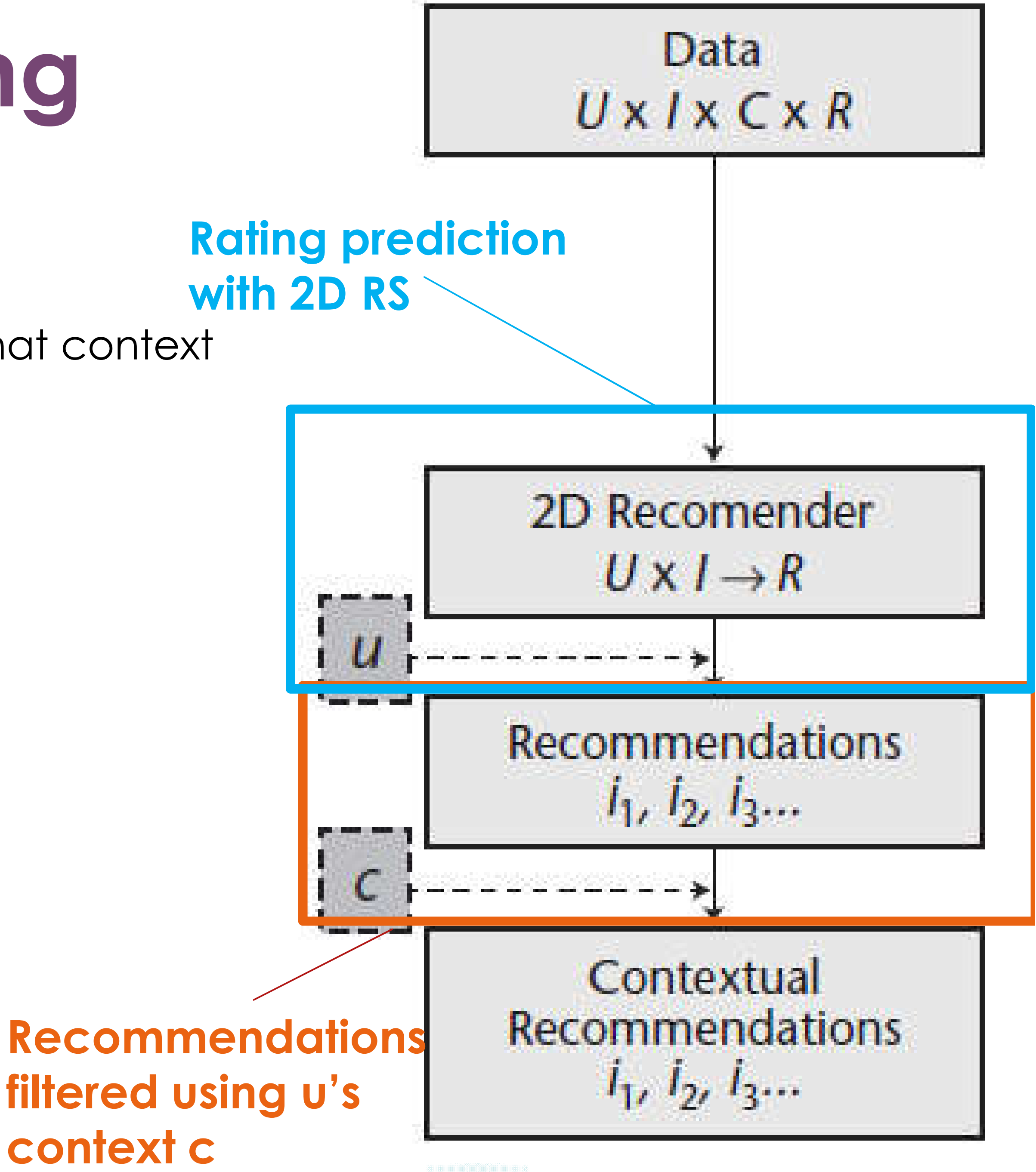
Rating prediction with 2D RS

- Example: movie recommender
  - c = (*Saturday*)
  - c = (*Girlfriend, Theatre, Saturday*)



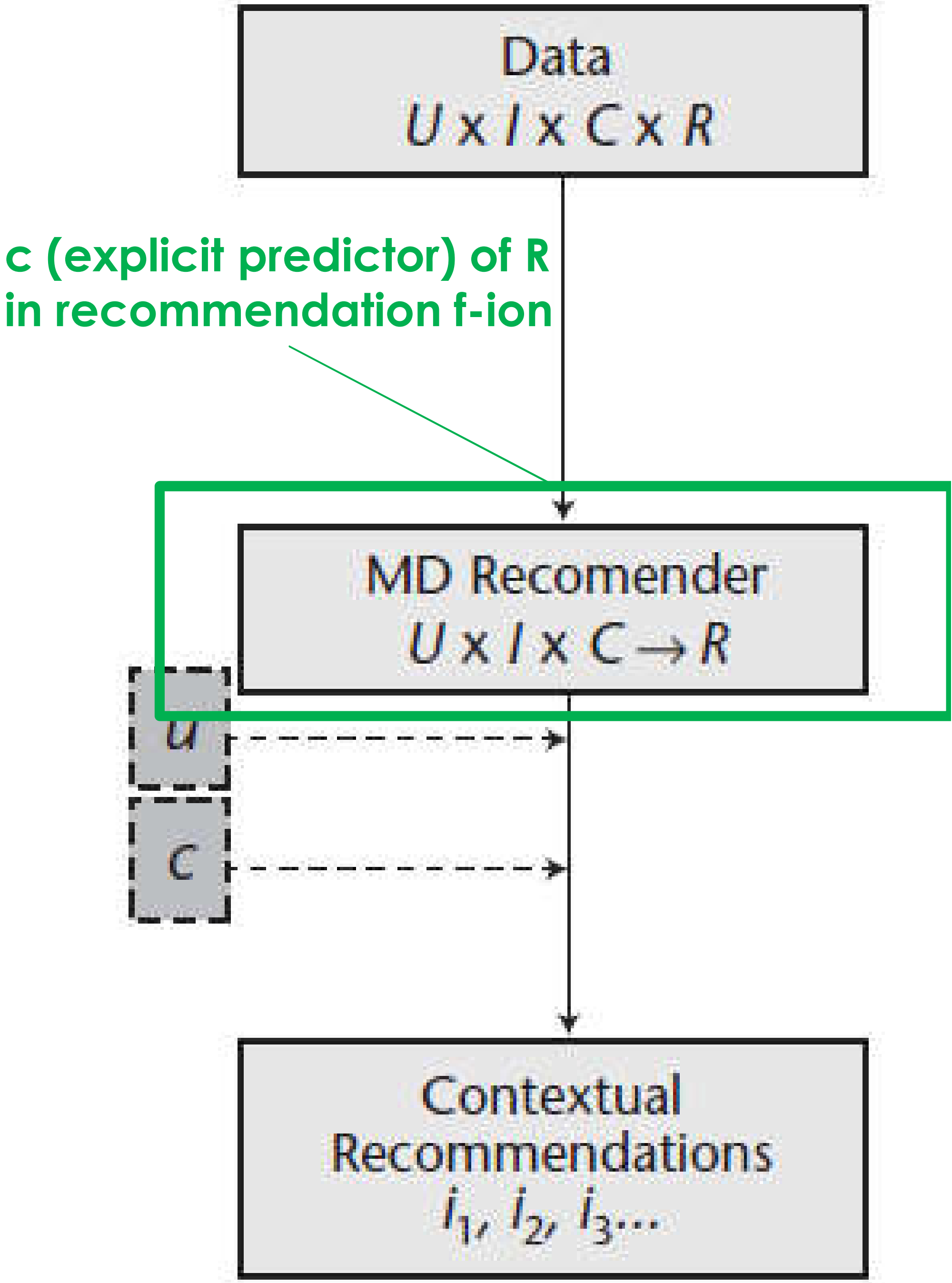
Contextual post-filtering

- Approaches
  1. filtering out irrelevant recommendations in that context
  2. adjusting ranking
- Techniques
  - heuristic
    - Find common item attributes for u in c
    - Filter recommendations
  - model-based
    - build predictive models
    - calculate probability of u choosing i type in c
    - adjust recommendations
- E.g: movie recommender
  - c = *(weekend)* -> u –> comedies



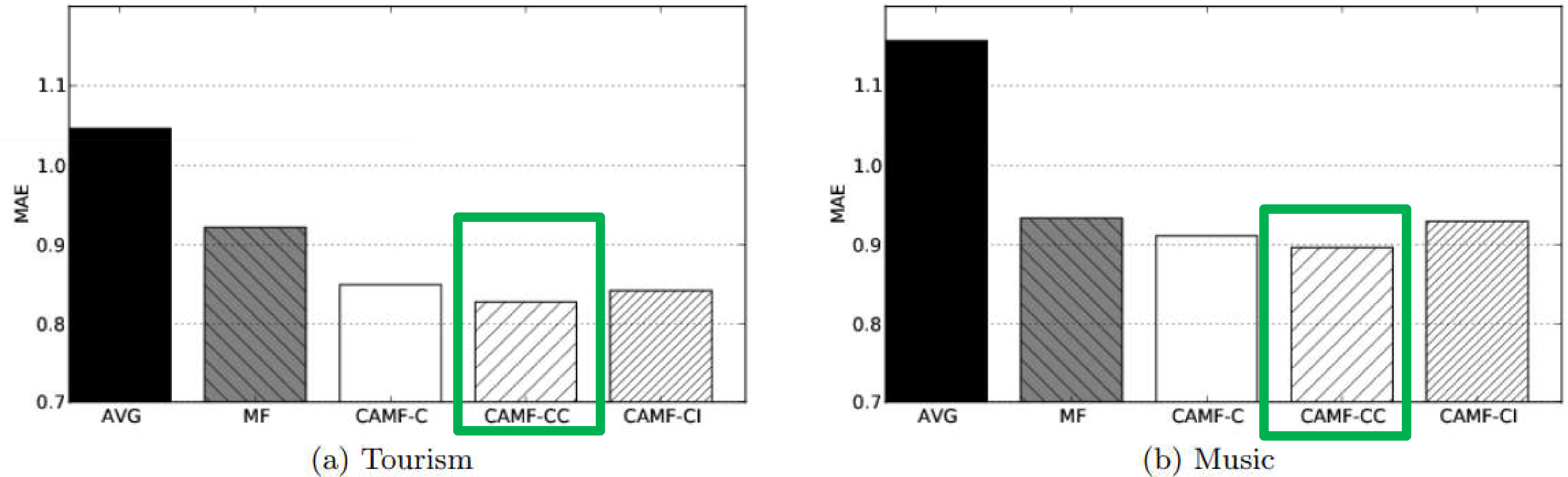
Contextual modelling

- MD functions
  - Predictive models
  - Heuristic
- Example: [restaurant recommender]
  - Support vector machine classification
    - Liked / disliked items
    - in different c
    - two sets of vectors in *n*-D space



Context-aware **Matrix Factorisation,** *Baltrunas (2011)*

- CAMF-C: 335 parameters
  - single parameter for each contextual condition
- CAMF-CC: 547
  - one model parameter for each contextual condition and item category
- CAMF-CI: 1395
  - one parameter per contextual condition and item pair



Evaluation methods

- Predictive accuracy
- Precision, Recall, F1 Score
- User satisfaction
- HitRate = #hits / #recs
- Model complexity
- Data sparsity
- Domain properties
- *See Villegas (2018)*

Source: Adomavicius (2011), Wang (2018), Villegas (2018)

Applications / Research

CA music recommendations, Wang (2018)

- partially observable & unobservable context
- neural network models
  - Infer preference from listening sequence
- **Contextual modelling**
- Prediction with collaborative filtering (cosiine similarity) using learned embeddings

Context-sensitive mobile information search, *Church et al. (2007)*

- ***Post-filtering* model**
  - support users in browsing through community search experiences

Movie recommendations, *Cui (2018)*

- Time as context
- **Post-filtering**
  - context-aware two-level SVD

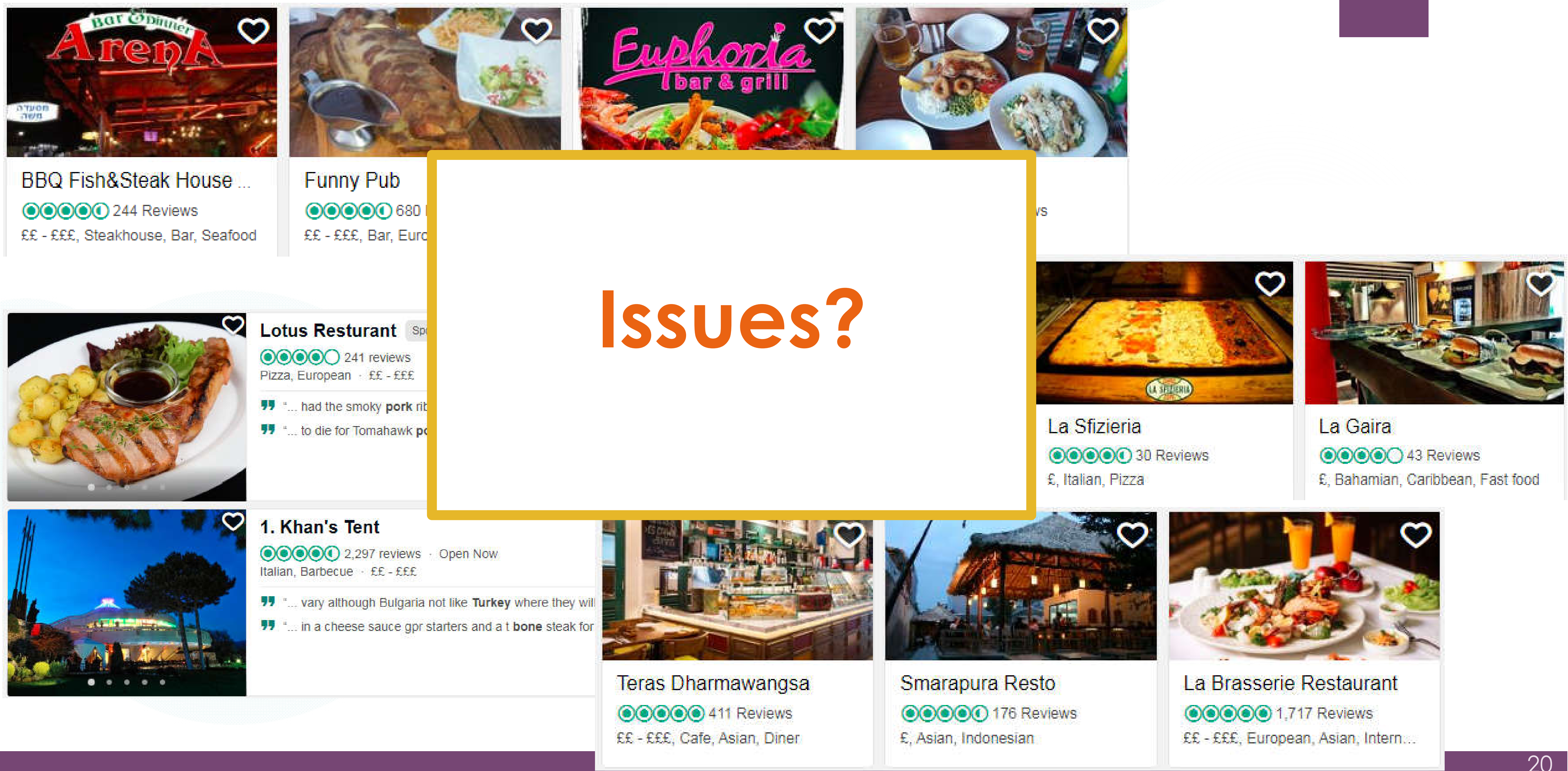
Restaurant recommendations, *Park, Hong, and Cho (2007)*

- **modelling approach** (Bayesian network)
  - weighted sum of conditional probabilities of restaurant's attribute values
- user's physical context (season, time of the day, position, weather, temperature)

Online travel RS, *Mahmood, Ricci, and Venturini (2010)*

- Markov decision processes + reinforcement learning
- Interaction media context

Task 2: CARS for restaurants



Issues?

Task 2.1: Contextual situation

- Identify / specify the context of a user seeking restaurant recommendations

G1. Physical context	G2. Social context	G3. Interaction media context	G4. Modal context
• Time, position, user's activity, weather, light, temperature, etc.	• alone or in a group, role of other people, etc.	• device used, type of media, etc.	• current psychological state, intentions, etc.

Task 2.2: Data collection

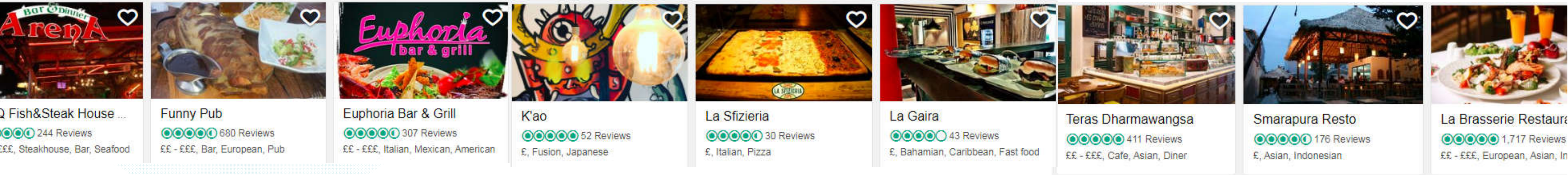
- Identify methods / tools / approaches to collect the contextual data
  - Explicit
  - Implicit

G1. Social context	G2. Interaction media context	G3. Modal context	G4. Physical context
• alone? • other people?	• device • type of media	• psychological state • intentions	• time • position • weather • light

Task 2.3: Contextual recommendations

- Consider how to apply a CARS technique for filtering/modelling
- How would it affect the list of recommendations?

• Pre-filtering	• Post-filtering	• Modelling *(Bayesian network)*	• Modelling *(SVM)*
G1. Interaction media context	**G2. Modal context**	**G3. Physical context**	**G4. Social context**



Key topics to take away

- Context Types
- Contextual situation
- Predicting r_{uic}
- Paradigms for integrating contextual information
  - Pre-filtering
  - Post-filtering
  - Modelling
- Evaluation methods
- Applications

References and reading material

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