Context-aware recommendation

Eirini Kolomvrezou, Hendrik Heuer
Special Course in Computer and Information Science
User Modelling & Recommender Systems
Aalto University

Context-aware recommendation

"You wouldn't like Peanuts when he's angry."

Recommendation Problem

Estimate ratings for **items** that have **not been seen** by a **user**

But: It is not enough to only consider users and items

On a weekday, a user might be
interested in world news and the stock market

On the weekend, she might be
interested in movie reviews and shopping

Properties of a Context-Aware System

Complexity

Recommendations are significantly more complex

Interactivity

The system needs ways to detect the context

Sparsity

There might not be enough data available

What is context?

Definition: "Context (...) **any piece of information** that is **relevant** for a user's **interaction** with a system, e.g. on individuality, location, time, relations and activity"

Multifaceted concept, many different definitions across various disciplines

Problem of **content discovery**

What is context?

Representational view, predefined by a set of observable attributes (a priori)

Interactional view, assuming an underlying context and that the context itself is not necessarily observable

For the recommendation

- Temporal (*when to deliver*)
- Spatial (*where to deliver*)
- Technological (*how to deliver*)

What is context?

For the input data:

- Intent of a purchase
- Location, time and weather
- User's emotional status
- Companions
- Type of communication device

Wide range of attributes should initially be selected by a domain expert

Implicit capturing

New technical opportunities to implicitly observe the experience and capture the relevance values

Possible sources

- Calendar
- Conversations
- Activity streams of social networks

Mobile phones are personal devices

Explicit capturing

- Choosing the current context from an ontology
- By providing keywords
- Free-text comment (ambiguous)

Additional ways to getting feedback:

- 5-star Libert scale (directly computable)
- Thumbs up / thumbs down

Downside: Requires a user's attention

Inferring context

Statistical and data mining methods

Who has the TV remote (husband, wife, son, daughter)? Can be inferred by observing the TV programs watched

Design Space

users x **items** x **contexts** → **relevance**

Microprofiles: Split user profiles into several (possibly overlapping) subprofiles, each representing users in a particular context

Context-aware filtering

Contextual Pre-filtering (PreF)
Filter out irrelevant ratings before computing recommendations

Contextual Post-filtering (PoF)
Use context information to filter or re-rank the final set of recommendations

Contextual Modelling
Use contextual information inside the recommendation-generating algorithms

Context-aware filtering

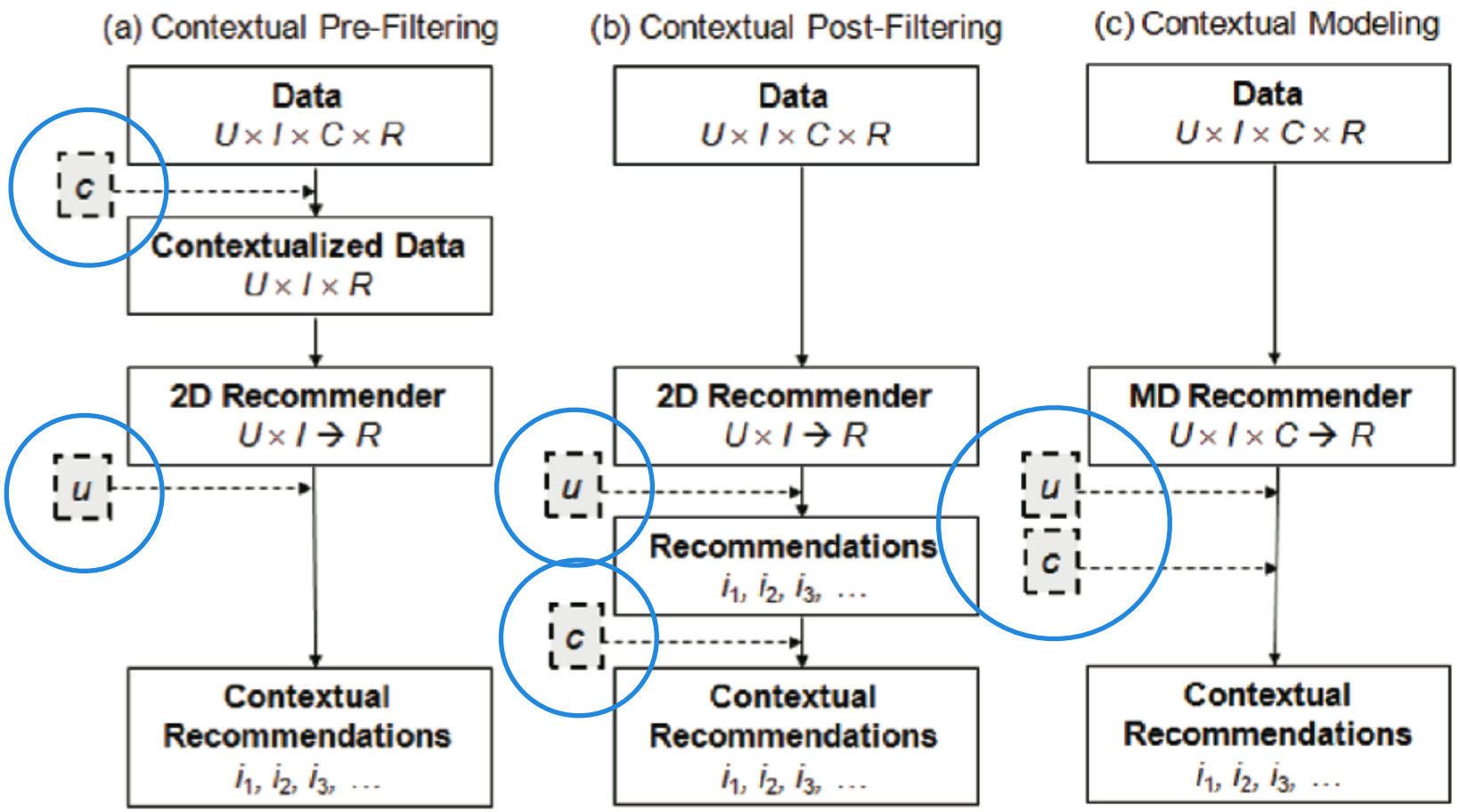
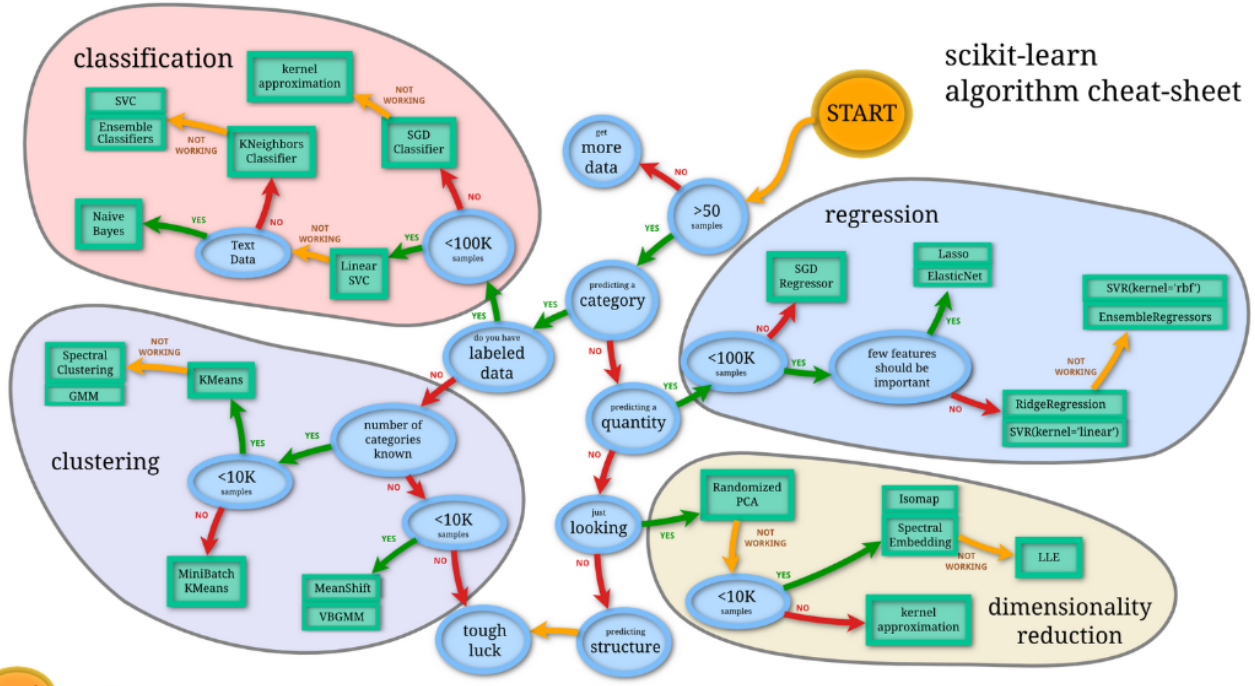


Fig. 7.4: Paradigms for incorporating context in recommender systems.

Context-aware filtering

Contextual Pre-filtering (PreF) and **Contextual Post-filtering** (PoF) have the major advantage that they allow using any of the numerous recommendation techniques



Back

Optimisation goals

Increasing **recall**, e.g. when users are looking for any good opportunities and may accept less useful recommendations

$$\text{Recall} = \frac{TP}{TP + FN}$$

Increasing **precision**, e.g. when users do not want to be bothered with useless recommendations

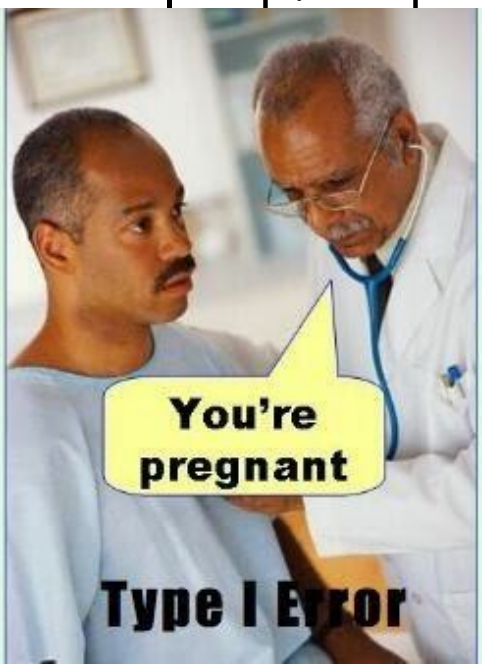
$$\text{Precision} = \frac{TP}{TP + FP}$$

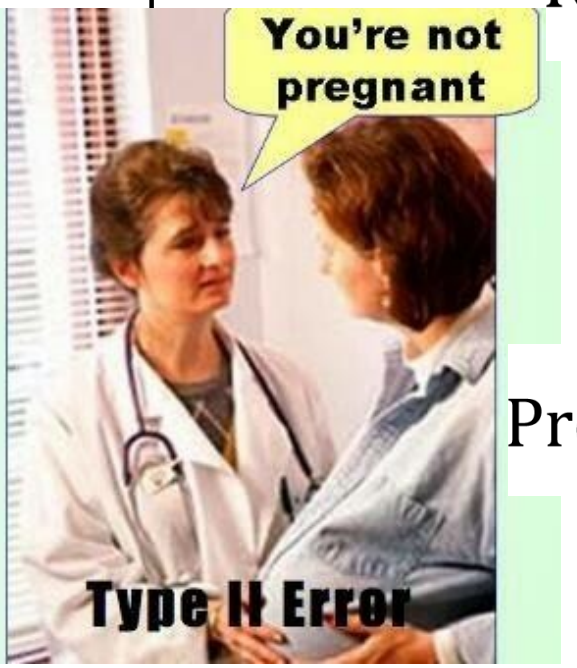
F-Score as harmonic mean between Precision & Recall

$$\text{F} = \frac{2}{\left(\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}\right)}$$

Optimisation goals

Increasing **recall**, e.g. when users





$$\text{Recall} = \frac{TP}{TP + FN}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{F} = \frac{2}{\left(\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}\right)}$$

FP

FN

Metrics

Diversity metrics include probability-based, logarithm-based and rank-based measures

Heterogeneity is measured by looking at how many items customers had purchased in each product category, i.e. by **computing the average entropy** of each customer's vector **of known ratings**

$$H = -\sum p(x) \log p(x)$$

Advantage

With traditional recommender systems, there is always a **trade-off** between **accuracy** and **diversity**

Context-aware recommender systems can **increase diversity while preserving accuracy**

Disadvantages

When the **context becomes finer**, the quantity of **information available** in each context **decreases**

Contextual Post-filtering is the **least affected**, because it doesn't take the contextual information into account

Commercial relevance

Companies: Netflix, Amazon, Linkedin, Spotify
Industries: music, movies, travel and tourism

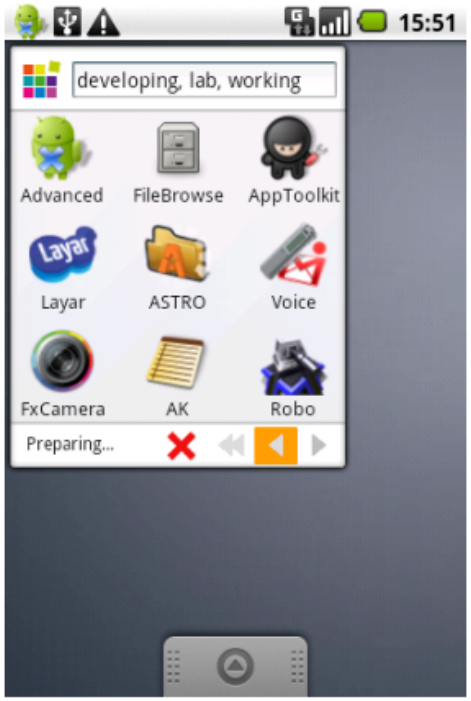
Different contexts require different recommendation strategies

Challenges:

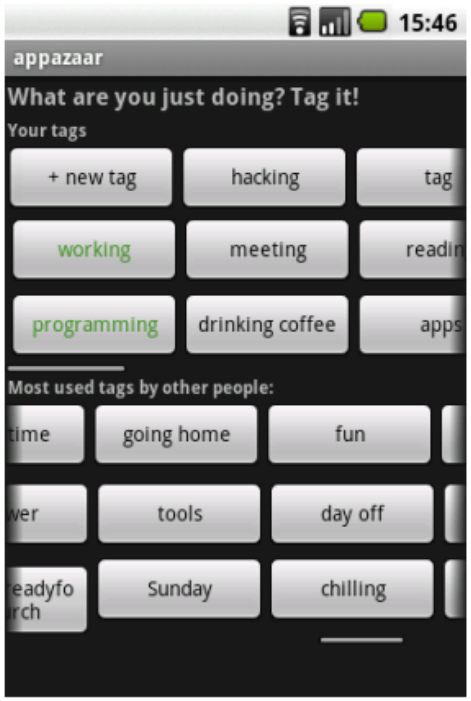
- Developing novel data structures
- Efficient storage methods
- New system architectures

Case Study

- Logger - capturing user's identity
- Central unit - running an inference engine
- User interface - offering recommendations



)



c)

Case Study

Collaborative Filtering applied to movies

Context includes **time** (weekend, weekday, opening weekend), **place** (movie theater, home) and **companion** (alone, with friends, with girlfriend / boyfriend, with family)

Table 7.2: High-performing large contextual segments.

Segment	CF: Segment-trained F-measure	CF: Whole-data-trained F-measure
Theater-Weekend	0.641	0.528
Theater	0.608	0.479
Weekend	0.542	0.484

Case Study Methodology

Simulated purchase on **Amazon**

In each session, the user specified the context and intent of purchase (personal use or gift and for whom)

Datasets

DSet 1: Simulated navigating and purchasing on Amazon (Palmisano et al., 2008)

DSet 2: European e-commerce website with ~120,000 users with time of the year a contextual variable, of which 40,000 users were used

DSet 3: E-commerce website that sells comics and comic-related products with 50,000 transactions and 5,000 users, with category as the contextual variable

Type of data set

	DSet 1	DSet 2	DSet 3
Sparsity	low	medium	high
Heterogenity	high	medium	low

Table 1. Type of data represented by sparsity and heterogeneity in the User-Item-Context matrix

Type of data	Sparsity (S)	Heterogeneity (H)
DSet 1	52%-71%	65.63%
DSet 2	82%-86%	29.50%
DSet 3	98%-99%	9.79%

Post Filtering

- Exploits all information available to generate recommendations (via contextual matrix)
- Uses context to filter out recommendations
- Generates the most diverse recommendations
- Provides high diversity but poor accuracy

Post Filtering

It was shown that when the **post-filtering** method is realized in the **right way**, it constitutes the **best-of-breed contextual method**

On the other hand, **if** it is realized **in a poor way**, it can be the **worst contextual method**

Combining multiple approaches

Often a **combination** (a "blend" or an **ensemble**) provides significant performance improvements

- Time information as pre-filtering
- Weather information as post-filtering

Popular example:
Netflix challenge

Combining multiple approaches

Recommend what to watch in the cinema

Pre-filter
recommender systems

Recommend what movie to watch at home

Traditional
recommender system

Results

Post Filtering dominates

- when the context is "Fine" and the data has low sparsity and high heterogeneity (DSet 1)
- with high sparsity and low heterogeneity (DSet 3)

Contextual Modelling (CM) dominates

- with medium levels of sparsity and heterogeneity (DSet 2)

When customer behaviour is **heterogeneous** and the **quantity of information** is **high** (DSet 1), **all** approaches **generate diverse recommendations**

Results

Maximizing both accuracy and diversity is impossible

The most accurate context-aware systems tend to be the worst in terms of diversity

Context granularity only affects accuracy, not diversity

No clear winner in terms of Recall
(verified using the t-test => statistically significant)

Challenges

- Sparseness of data
- Scalability
- Cold start
- Short-term and long term interests
- Changing data (Old data is favored)
- Unpredictable items (items that are either loved or hated)

Recommendations

- Not every configuration makes sense
- Identify which method significantly dominates the others
- Favor implicit over explicit parameter capture
- "Roll up" to higher level concepts

  with father on Tuesday => with family member during week

Context-aware recommendation

Eirini Kolomvrezou, Hendrik Heuer
Special Course in Computer and Information Science
User Modelling & Recommender Systems
Aalto University