

## Week 11

# Course. Introduction to Machine Learning **Theory 11. Recommender Systems**

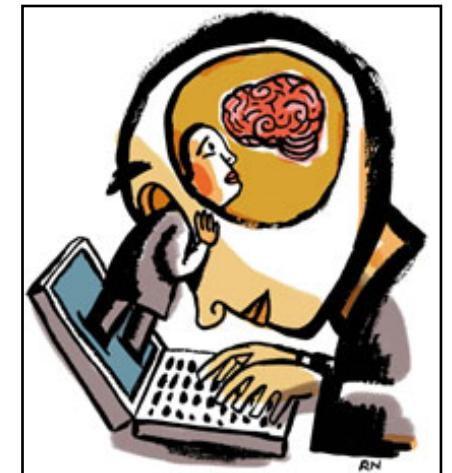
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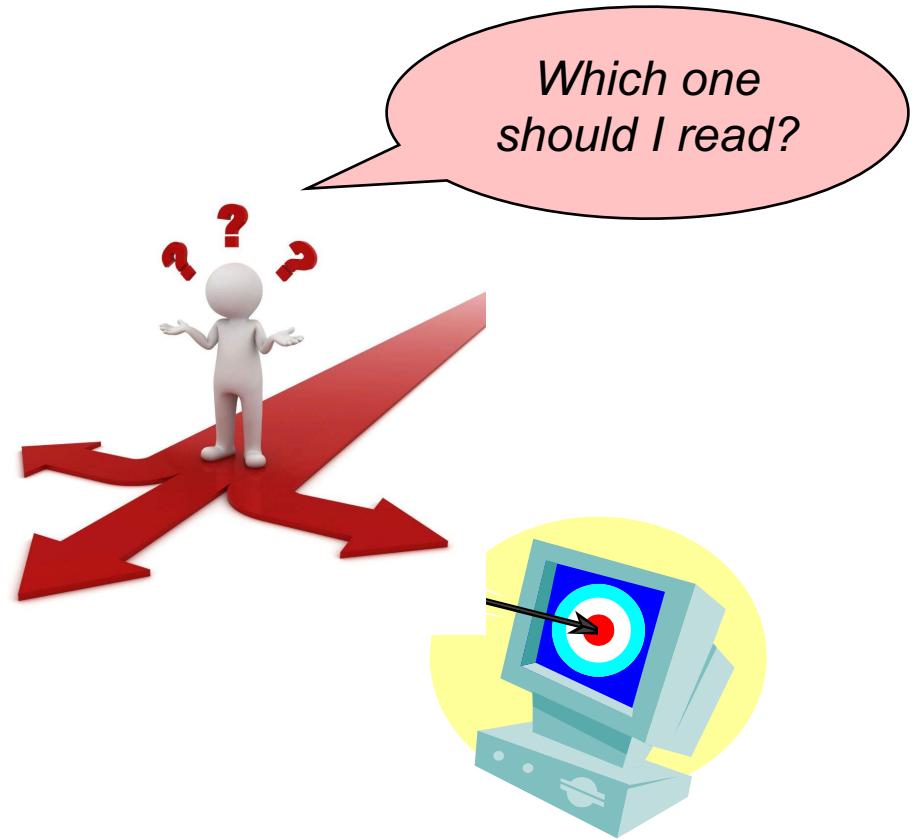
# Introduction to Recommender Systems



# Introduction to Recommender systems



***Recommendations  
from friends***



***Recommendations  
from Online  
Systems***

# Which one should I choose?



**Make a  
decision**

For example, IMDb contained in January 2018  
IMDb: 4.734.693 titles and 8.702.002 users

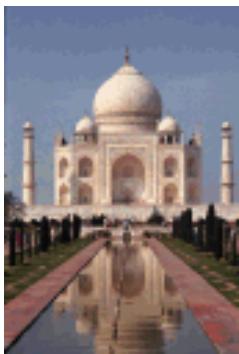
# What travel should I do ?



I would like to escape from this ugly and tedious work life and relax for two weeks in a sunny place. I am fed up with these crowded and noisy places ... just the sand and the sea ... and some "adventure".



I would like to bring my wife and my children on a holiday ... it should not be too expensive. I prefer mountainous places... not too far from home. Children parks, easy paths and good cuisine are a must.



I want to experience the contact with a completely different culture. I would like to be fascinated by the people and learn to look at my life in a totally different way.

# Information Overload

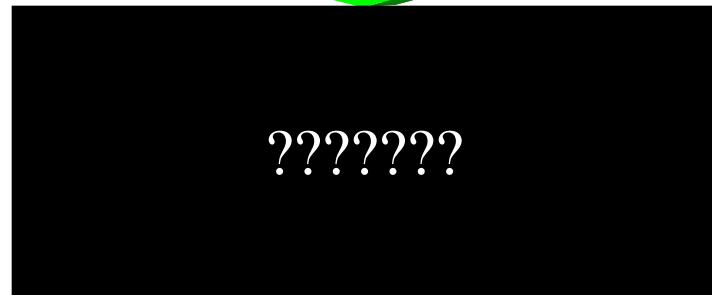
- **Internet = information overload**
  - the state of having too much information to make a decision or remain informed about a topic
- Information retrieval technologies can assist a user to **locate content** if the user knows exactly what he is looking for (with some difficulties!)
  - The user must be able to say “yes this is what I need” when presented with the right result
- But in many information search task, e.g., product selection, the user is...
  - not aware of the range of available options
  - may not know what to search
  - if presented with some results he may not be able to choose.

# Decisions

- When there are 100 million of options it is obvious we need tools for searching, filtering, ranking options
- *But even when there are a few dozen of options we need support*
- **Examples**
  - Where to go for dinner tonight?
  - What flight for going to London?
  - What Digital camera should I buy?



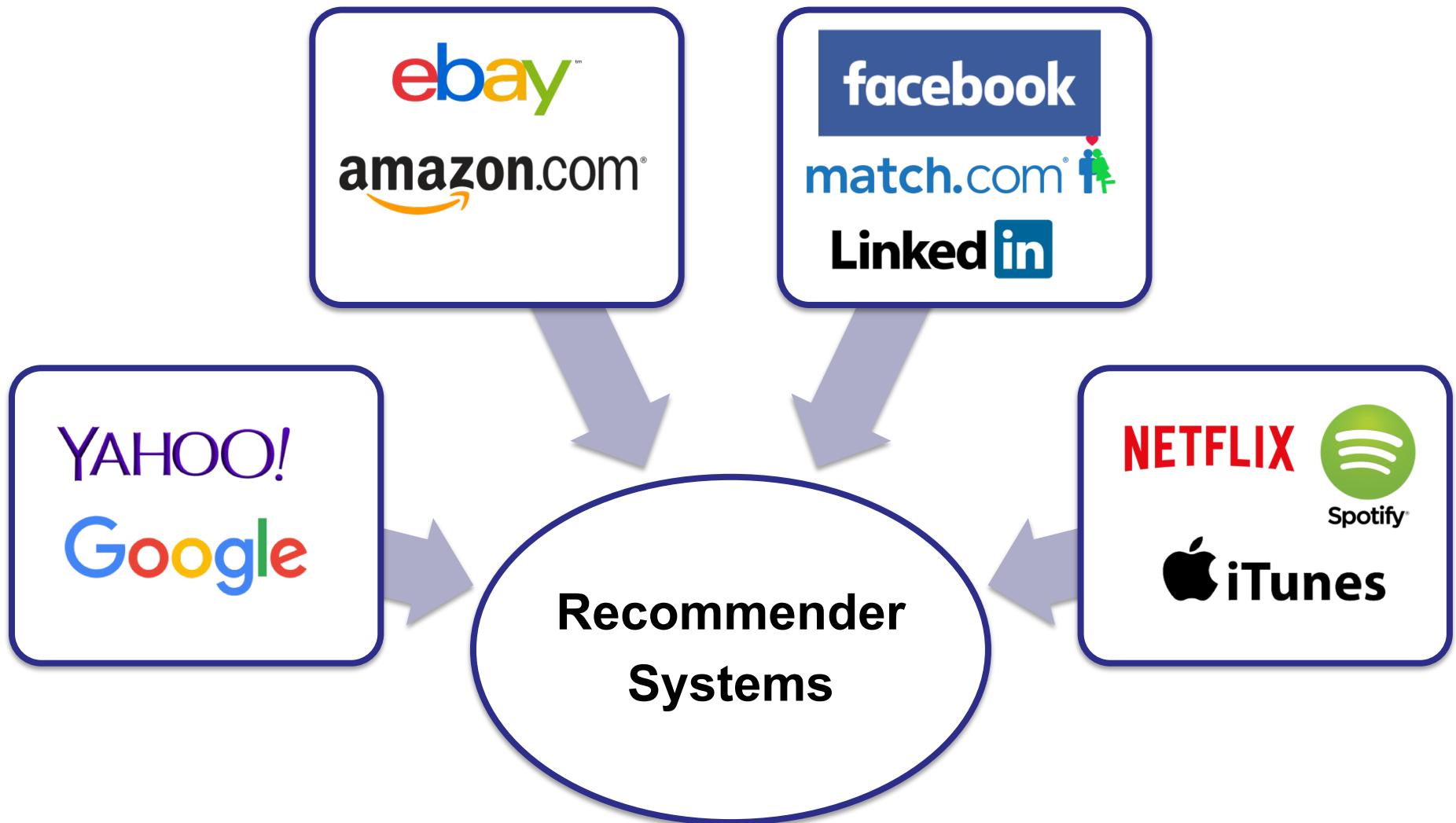
# A Solution



- A **recommender system** helps to make choices without sufficient personal experience of the alternatives
  - To **suggest products** to their customers
  - To provide consumers with **information to help them decide** which products to purchase
- They are based on a number of **technologies**: information filtering, machine learning, adaptive and personalized system, user modeling, intelligent user interfaces, ...

- Automates quotes like:
  - "I like this book; you might be interested in it"
  - "I saw this movie, you'll like it"
  - "Don't go see that movie!"
- Many of the top commerce sites use recommender systems to improve sales
- Users may find new books, music, or movies that were previously unknown to them
  - Also can find the opposite for e.g., movies or music that will definitely not be enjoyed

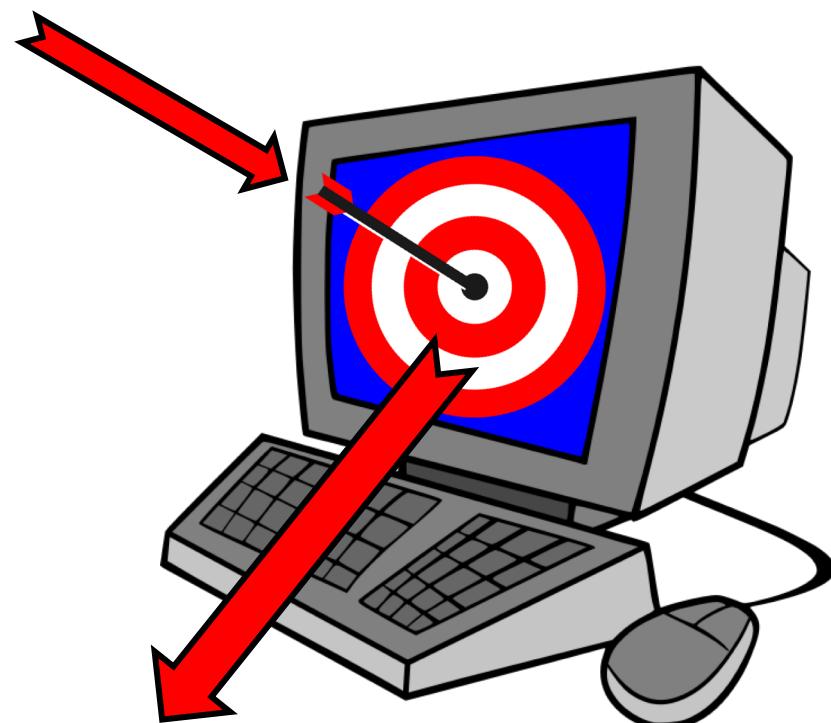
# Use of RecSys



# Basic interaction paradigm of RecSys

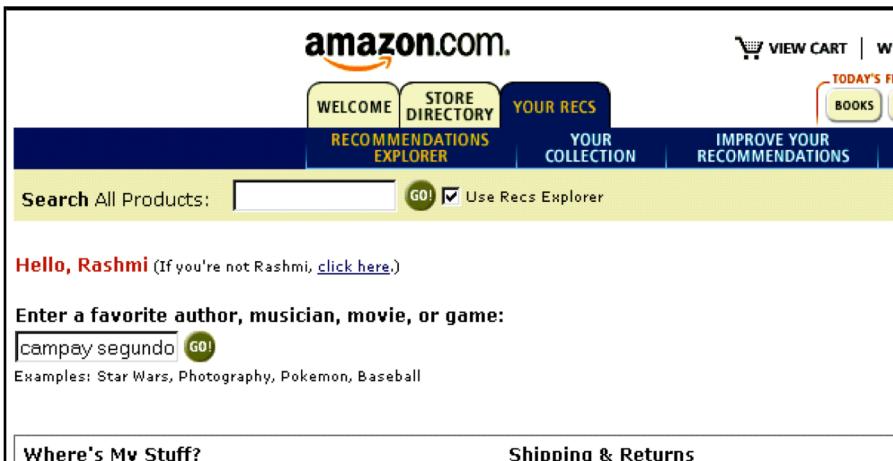


**Input (ratings of movies):**  
“I recently enjoyed *Harry Potter, Star Wars, Joker*”



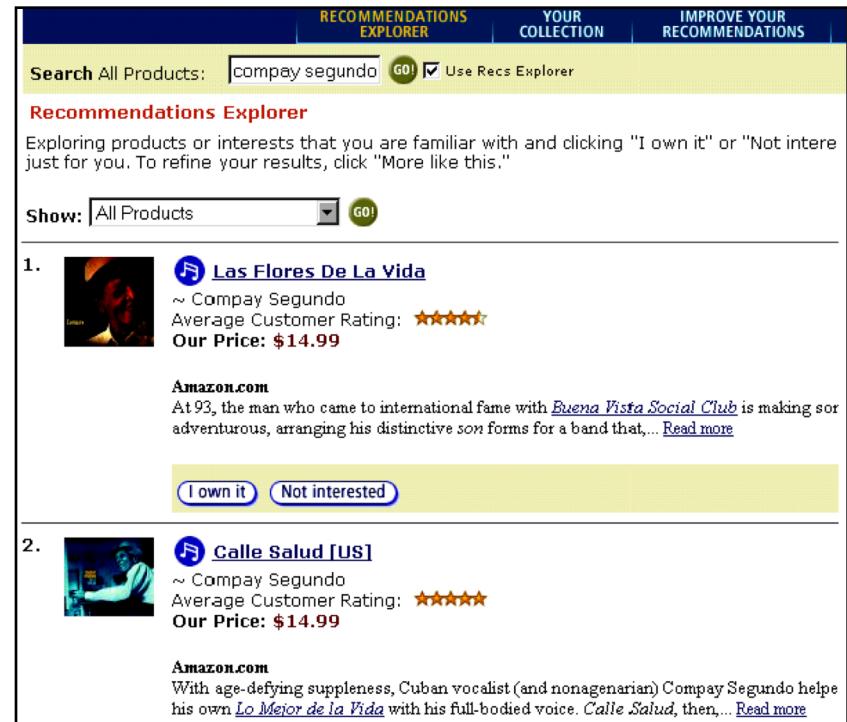
**Output (Recommendations):**  
“Movies you might enjoy are... ”

# Amazon's Recommendation Process



The screenshot shows the Amazon.com homepage. At the top, there is a navigation bar with links for "WELCOME", "STORE DIRECTORY", "YOUR RECS", "YOUR COLLECTION", and "IMPROVE YOUR RECOMMENDATIONS". Below the navigation bar, there is a search bar with the placeholder "Search All Products:" and a "GO!" button. To the right of the search bar is a checkbox labeled "Use Recs Explorer". Further down, there is a message "Hello, Rashmi" and a section for entering a favorite author, musician, movie, or game, with "campay segundo" entered and a "GO!" button. Below this, there is a "Where's My Stuff?" link and a "Shipping & Returns" link.

**Input:** One artist/author name



The screenshot shows the "RECOMMENDATIONS EXPLORER" results for the query "campay segundo". The results are displayed in a list format. The first result is "Las Flores De La Vida" by Compay Segundo, which has an average customer rating of 4.5 stars and a price of \$14.99. The second result is "Calle Salud [US]" by Compay Segundo, also with an average customer rating of 4.5 stars and a price of \$14.99. Both results include a "I own it" and "Not interested" button below them.

**Output:** List of recommendations  
Opportunity to Explore / Refine

# The recommendation process from the user's perspective

User inputs  
preferences...

Time and effort  
to input  
Privacy concerns

...receives  
recommendations...

Time and  
effort to  
review recs

...and decides if he/she will  
sample recommendation

In the end, a user benefits only  
if recommendations turn out to  
be good ones.



# What Users Want

Fast

Engaging

New to me

**PROCESS**

Easy

**RECOMMENDATIONS**

Good

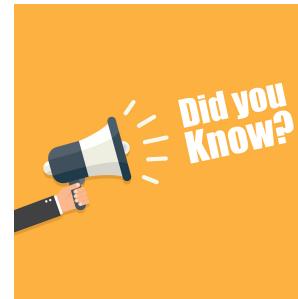
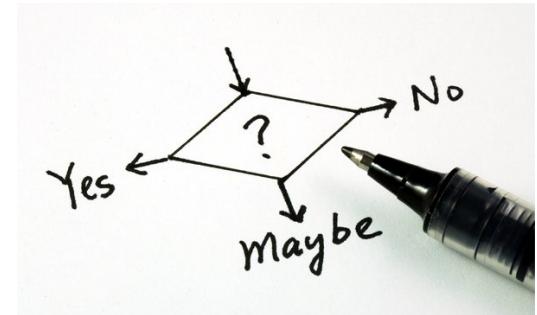
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To succeed, collaborative filtering recommender systems  
need a LOT of motivated regular users

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# Objective of RecSys

- Help people **make decisions**
  - Where to spend attention
  - Where to spend money
- Help **Maintain awareness**
  - New products
  - New information



In both cases: Many options, limited resources

# Definition of Recommender

- Recommender systems are a specific type of **information filtering** technique that attempt to present to the user information **items** (movies, music, books, news, web pages) the **user is interested in**. To do this the **user's profile** is compared to some reference characteristics

from:

[http://en.wikipedia.org/wiki/Recommendation\\_system](http://en.wikipedia.org/wiki/Recommendation_system)

# Recommender definitions

- Recommender systems are personalized **information systems** that provide recommendations: suggestions for items likely to be of use to a user (Burke, 2007)
- **Recommendation as a prediction problem** (Celma & Lamere, 2007)
  - Attempt to predict items that a user might be interested in
  - compute *similarity* between objects
    - user-user
    - item-item
  - form *predictions* based on the computed similarities

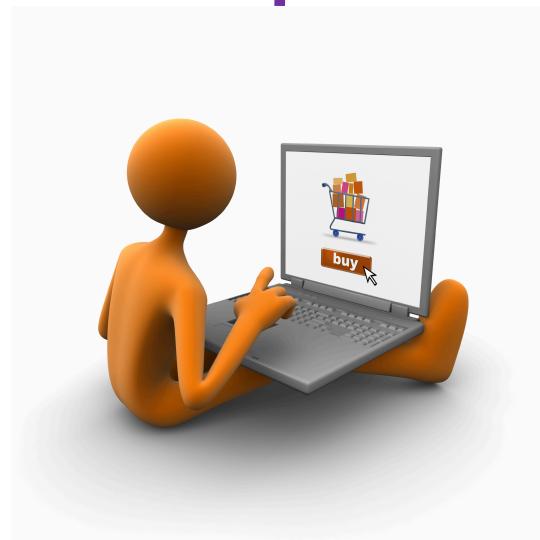


# Recommendation techniques

# Single Recommenders

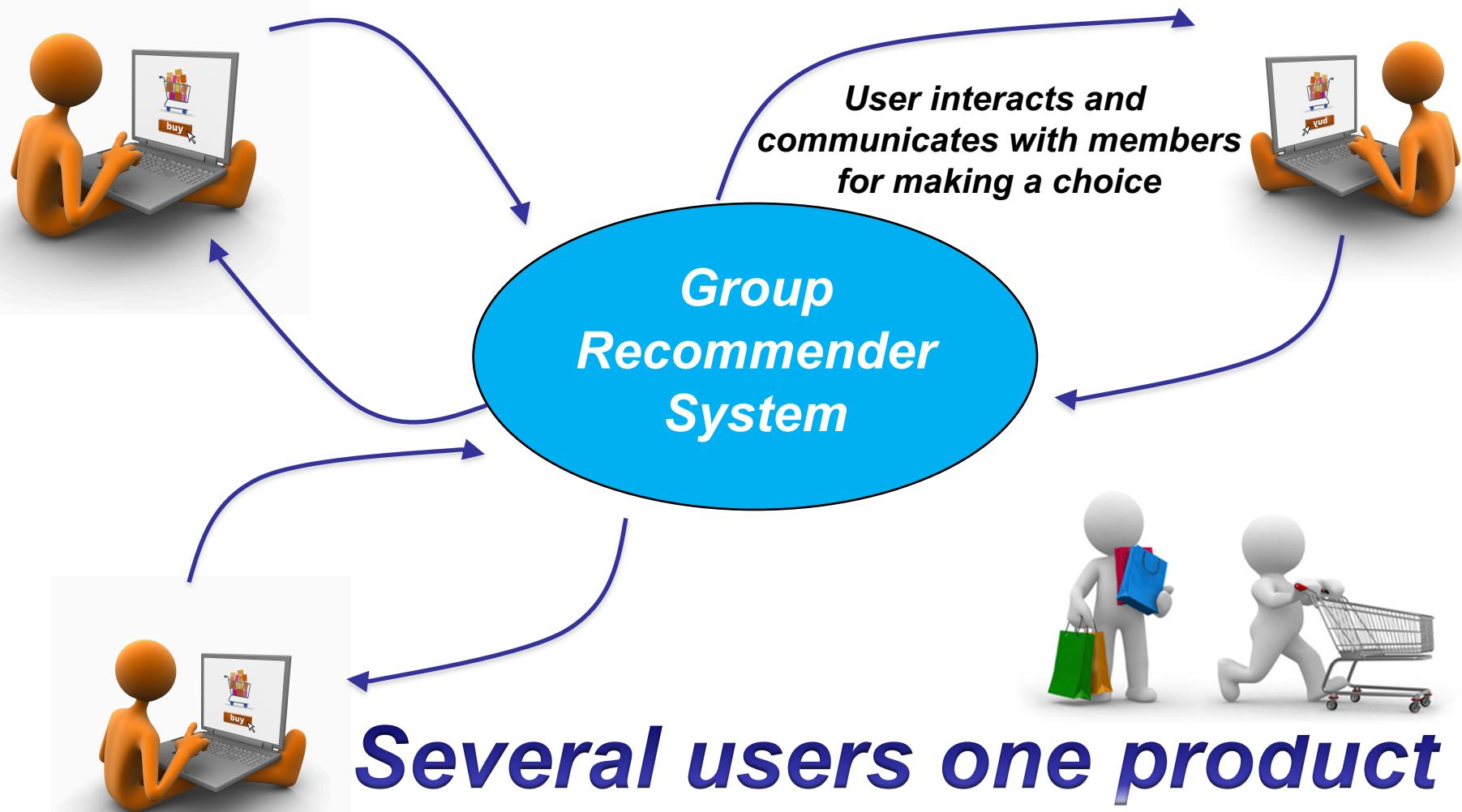
*Single  
Recommender  
System*

***User interacts  
for making a choice***



***One user one product***

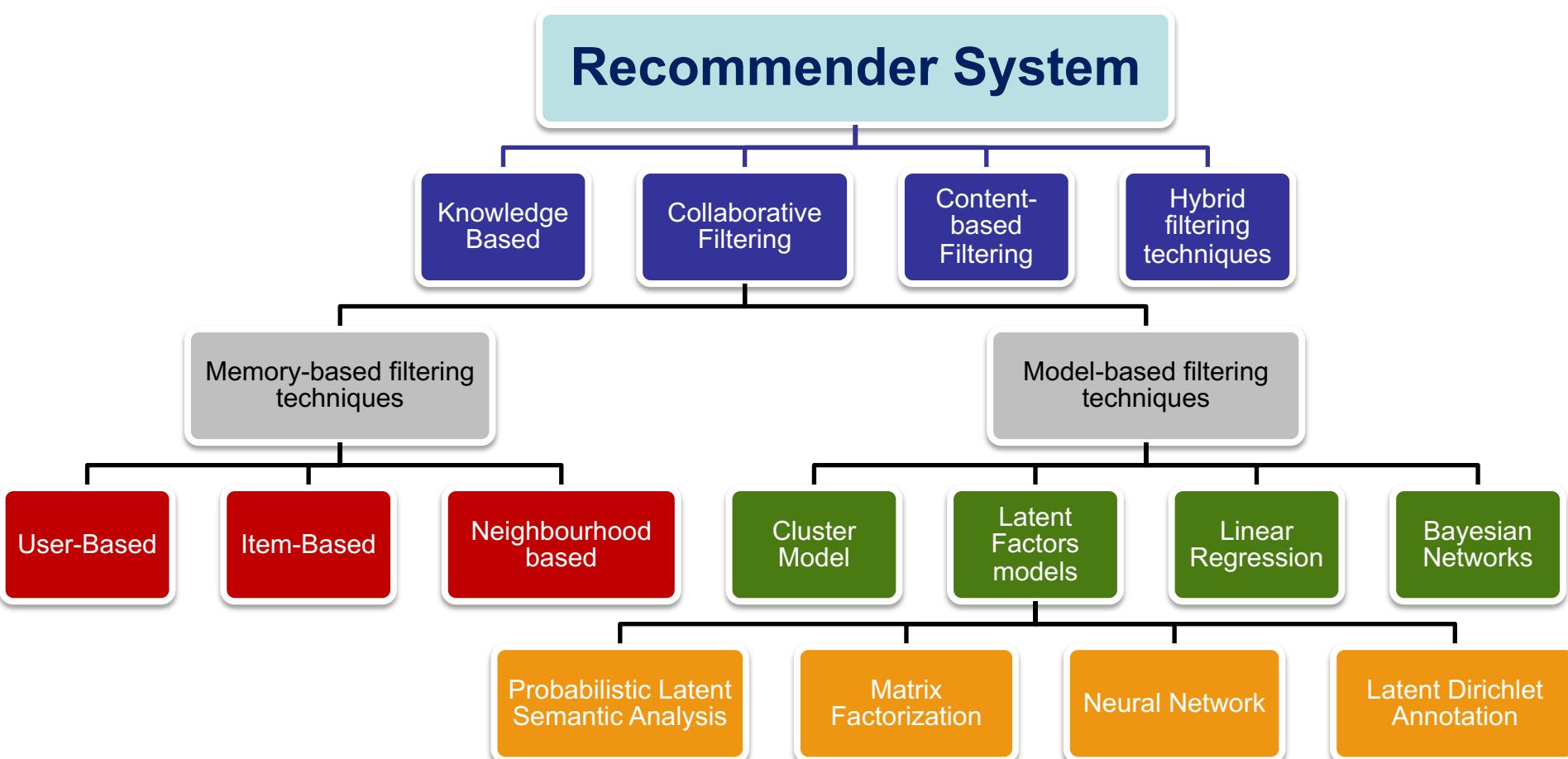
# Group Recommenders



## Objective

- Address recommendations to groups of users
- First we have to **identify user's individual preferences**
- Second, we try to find a **compromise that is fair** and **acceptable** to all the users





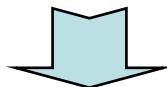
# Recommendation techniques

- **Knowledge-based (KB)** – knowledge about users and products used to reason what meets the user's requirements, using discrimination tree, decision support tools, case-based reasoning (CBR)
- **Collaborative Filtering (CF)** – aggregation of consumers' preferences and recommendations to other users based on similarity in behavioral patterns
- **Content-based (CN)** – supervised machine learning used to induce a classifier to discriminate between interesting and uninteresting items for the user
- **Hybrid filtering techniques** – combine one or more of the techniques mentioned above

## Classification based on knowledge source

- **Knowledge-based (KB)**
  - Domain knowledge, product features, user's need/query
  - Inferences about user's needs and preferences
- **Collaborative (CF)**
  - User's ratings “only”
- **Content-based (CN)**
  - Product features, user's ratings
  - Classifications of user's likes/dislikes

- Context
  - What is context? Additional information, besides information on *Users*, that is *relevant* to recommendations
  - Relevant in:
    - Identifying pertinent subsets of data when computing recommendations
    - Building richer rating estimation models
    - Providing various types of constraints on recommendations outcomes



## Context-aware recommender systems

# Obtaining context

- Explicitly specified by the user
  - E.g., I want to watch a movie at home with my parents
- Observed or deduced by the system
  - Time (from system clock)
  - Location (from GPS)
  - Deduced from user's behaviour
- How to obtain the context is a separate problem that lies beyond the scope of this course
  - Context-aware recommender systems are very important for mobile computing

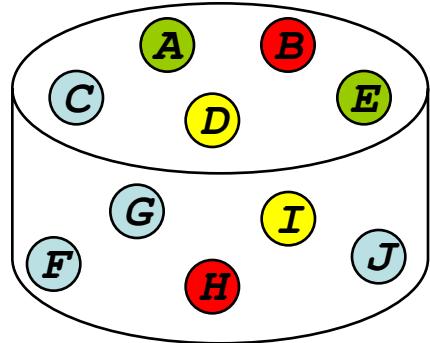
- **Cold-start problem** – concerns the issue that the system cannot draw any **inferences** for **users** or items about which it has not yet gathered sufficient information
- **Latency problem** – new items incorporated into a Rec cannot be used in CF recommendations before a substantial amount of users have evaluated it

- **Sparsity problem** – few users have rated the same items
- **Gray-sheep problem** – refers to a user that fall on a border between existing cliques of users

# Summary of the techniques

- **Knowledge-based** methods go to the root of the decision problem
- **Collaborative-based** methods are the most popular
  - Suffers from bootstrapping problems
- **Content-based** methods are well rooted in information retrieval
- **Hybrid methods** are the most powerful and popular right now – there are plenty of options for hybridization

# Components of a recommender



**Choice Set**  
-Products  
-Web Pages  
-Movies  
-TV shows

...



**Recommender**  
*An algorithm that generates personalized recommendations*

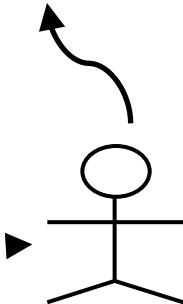
**Preference Profile for Target User**

*What the system “knows” about the user’s preferences*



**Preference Capture**

*The system learns about the user’s preferences*



**Target User**

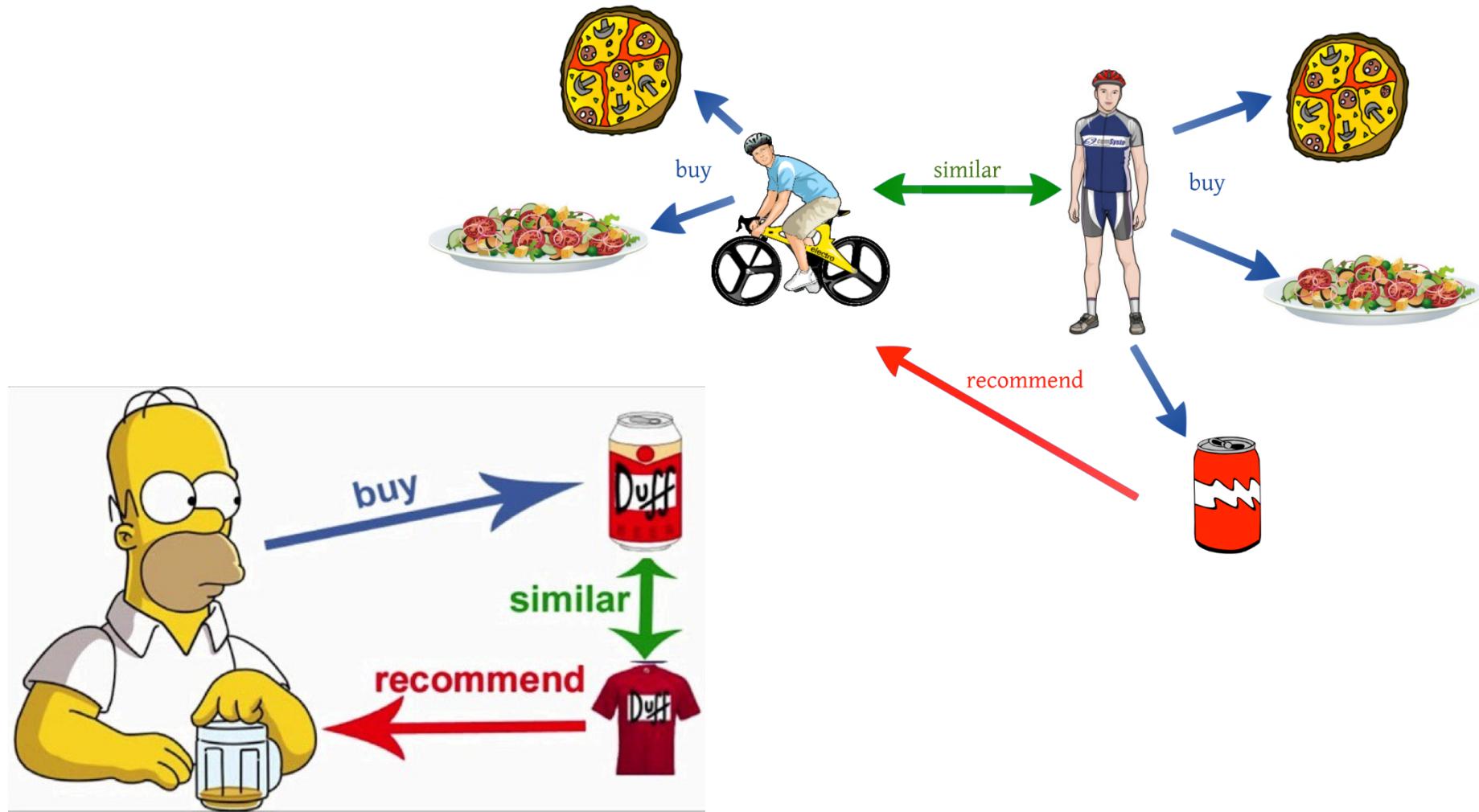
*Personalized Recommendations for Target User*

# An overview of Collaborative Filtering Recommenders

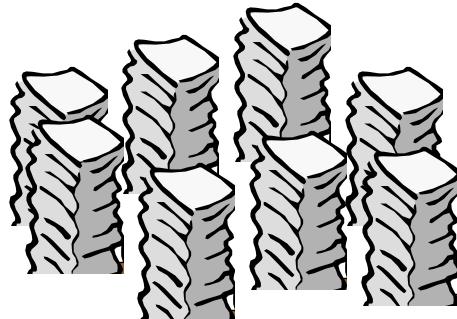




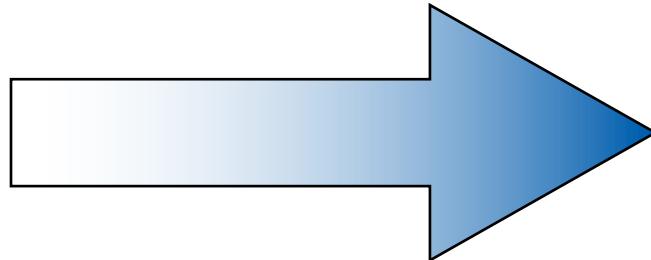
# Basic idea of RecSys



# Collaborative Filtering



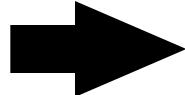
Unseen items



Community Opinions



Items you've  
experienced



Predictions



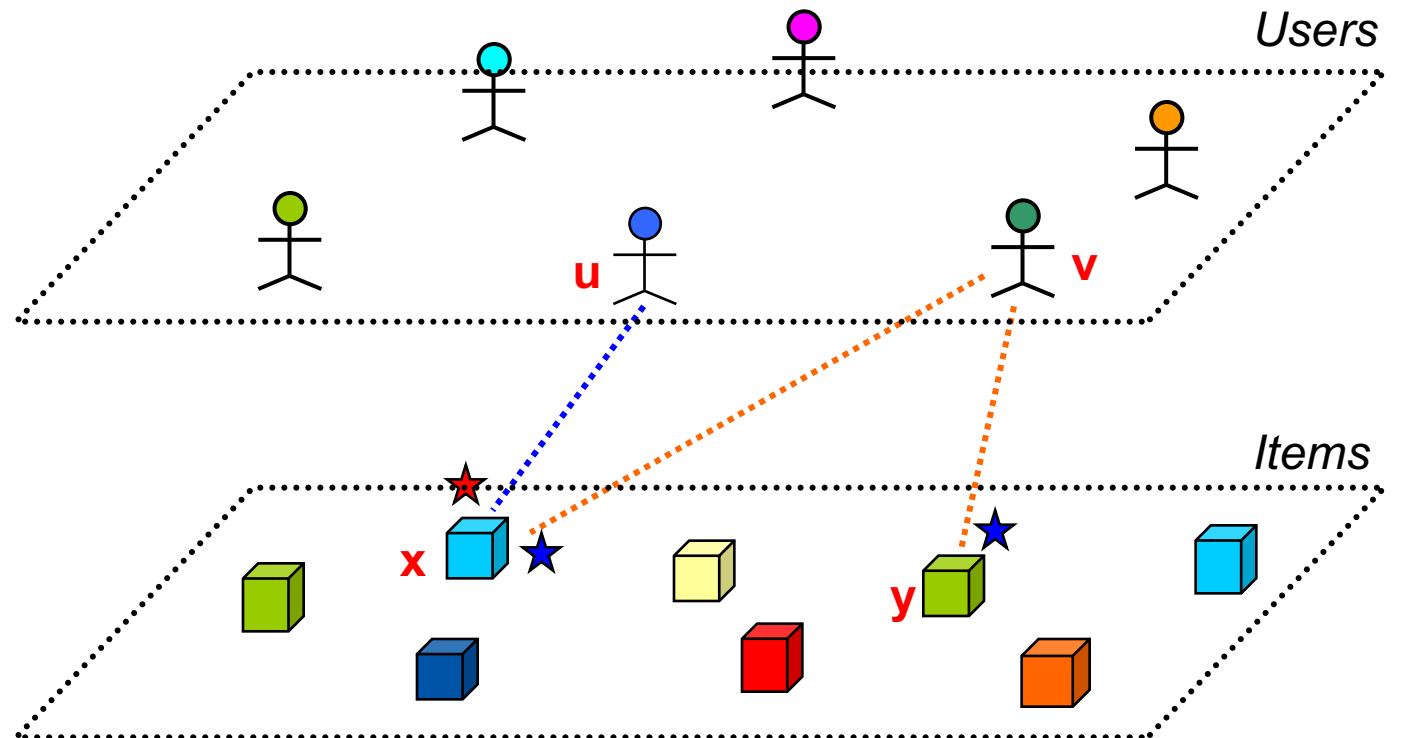
Your Opinions



Collaborative  
Filtering  
Process



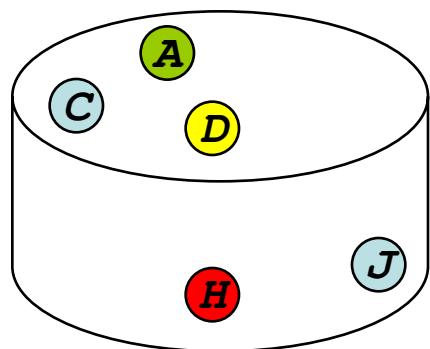
# Collaborative Filtering



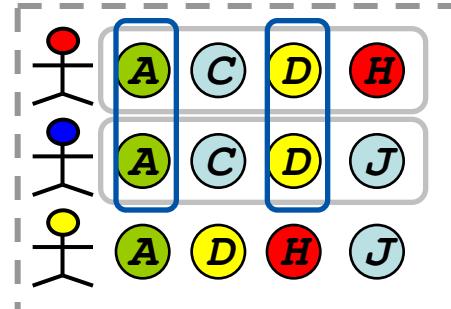
# Definition

- **Collaborative Filtering (CF)** is the process of filtering or evaluating items through the opinions of other people
  - Maintain a database of many users' ratings of a variety of items
  - For a given user, find other similar users whose **ratings** strongly correlate with the current user
  - Recommend items rated highly by these similar users, but not rated by the current user
  - Almost all existing commercial recommenders use this approach (e.g., Amazon)

# User-based



**Choice Set**  
LIMITED to those items selected, and/or purchased by users



**Recommender**  
Looks at profiles of “similar” users and recommends their most frequently selected or highest-ranked items

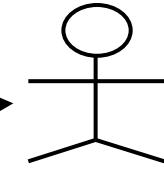
**Preference Profile for Target User**

Item C ✓



**Preference Capture**  
User selects Item C

C



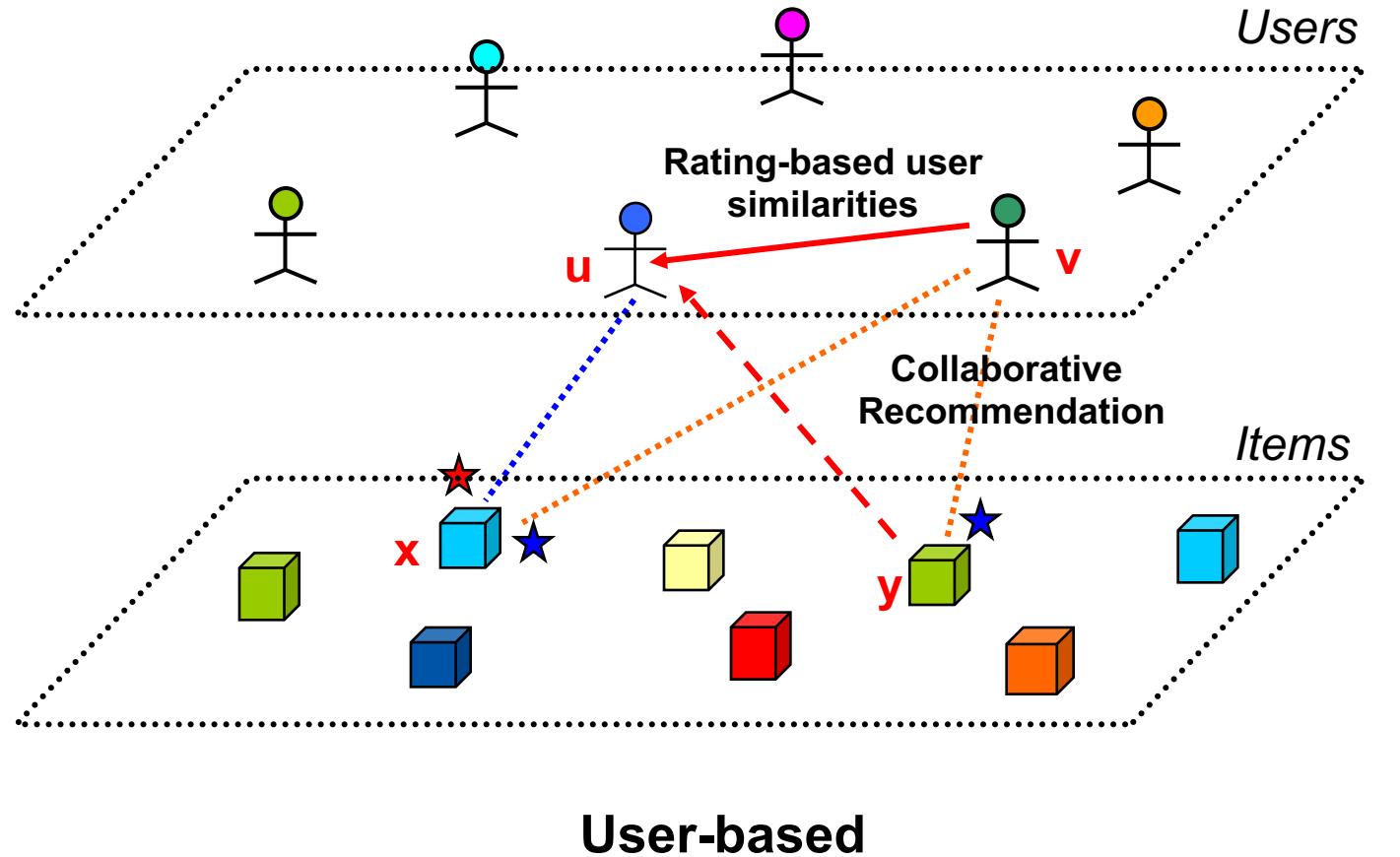
Personalized Recommendations for Target User

A  
D

**Target User**



# Collaborative Filtering



# Rating predictions

- Recommend to  $u$  those items ranked by  $v$  “similar” to  $u$

$$(a) \quad r(u, x) = c \sum_{v \in \eta(u)} sim(u, v) r(v, x) \quad \text{Similarity between users}$$

$$(b) \quad r(u, x) = \bar{r}(u) + c \sum_{v \in \eta(u)} sim(u, v) (r(v, x) - \bar{r}(v))$$

Predicted vote  
for “active  
user”  $u$   
is a weighted  
sum

$$\bar{r}(u) = \frac{1}{|S(u)|} \sum_{x \in S(u)} r(u, x) \quad S(u) = \{x \in \mathcal{I} \mid r(u, x) \neq \emptyset\}$$

$$c = \frac{1}{\sum_{v \in \eta(u)} |sim(u, v)|} \quad \text{Normalizing factor}$$

# Similarity between users

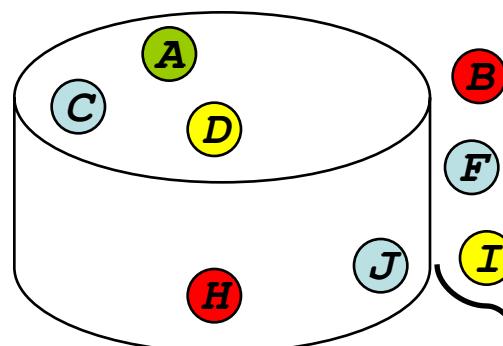
- The most popular approaches are:
  - **Cosine-based** user similarity (from IR)

$$\text{sim}(u, v) = \cos(r(u), r(v)) = \frac{\sum_{x \in \mathcal{I}} r(u, x)r(v, x)}{\sqrt{\sum_{x \in \mathcal{I}} r(u, x)^2 \sum_{x \in \mathcal{I}} r(v, x)^2}}$$

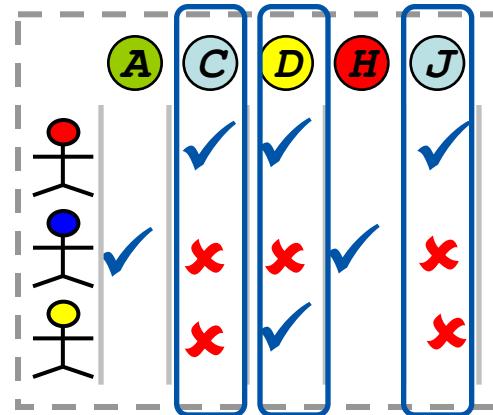
- **Correlation-based** user similarity (from GroupLens)

$$\text{sim}(u, v) = \frac{\sum_{x \in \mathcal{I}} (r(u, x) - \bar{r}(u))(r(v, x) - \bar{r}(v))}{\sqrt{\sum_{x \in \mathcal{I}} (r(u, x) - \bar{r}(u))^2 \sum_{x \in \mathcal{I}} (r(v, x) - \bar{r}(v))^2}}$$

# Item-based



**Choice Set**  
LIMITED to those items selected, and/or purchased by users



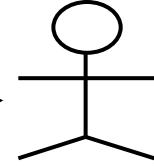
**Recommender**  
Looks at “similar” items and recommends those most frequently selected or highest-ranked

Personalized Recommendations for Target User

**Preference Profile for Target User**



**Preference Capture**  
User selects Item C



J

D

**Target User**

- Recommend to  $u$  items “similar” to those best ranked by  $u$

**Weighted  
sum**

$$r(u, x) = c \sum_{y \in S(u)} sim(x, y) r(u, y)$$

$$c = \frac{1}{\sum_{y \in S(u)} |sim(x, y)|}$$

# Similarity between items

## Cosine

$$sim(x, y) = \cos(r(x), r(y)) = \frac{\sum_{u \in \mathcal{U}} r(u, x)r(u, y)}{\sqrt{\sum_{u \in \mathcal{U}} r(u, x)^2 \sum_{u \in \mathcal{U}} r(u, y)^2}}$$

## Pearson

$$sim(x, y) = \frac{\sum_{u \in \mathcal{U}} (r(u, x) - \bar{r}(x))(r(u, y) - \bar{r}(y))}{\sqrt{\sum_{u \in \mathcal{U}} (r(u, x) - \bar{r}(x))^2 \sum_{u \in \mathcal{U}} (r(u, y) - \bar{r}(y))^2}}$$

## Adjusted Cosine

$$sim(x, y) = \frac{\sum_{u \in \mathcal{U}} (r(u, x) - \bar{r}(u))(r(u, y) - \bar{r}(u))}{\sqrt{\sum_{u \in \mathcal{U}} (r(u, x) - \bar{r}(u))^2 \sum_{u \in \mathcal{U}} (r(u, y) - \bar{r}(u))^2}}$$



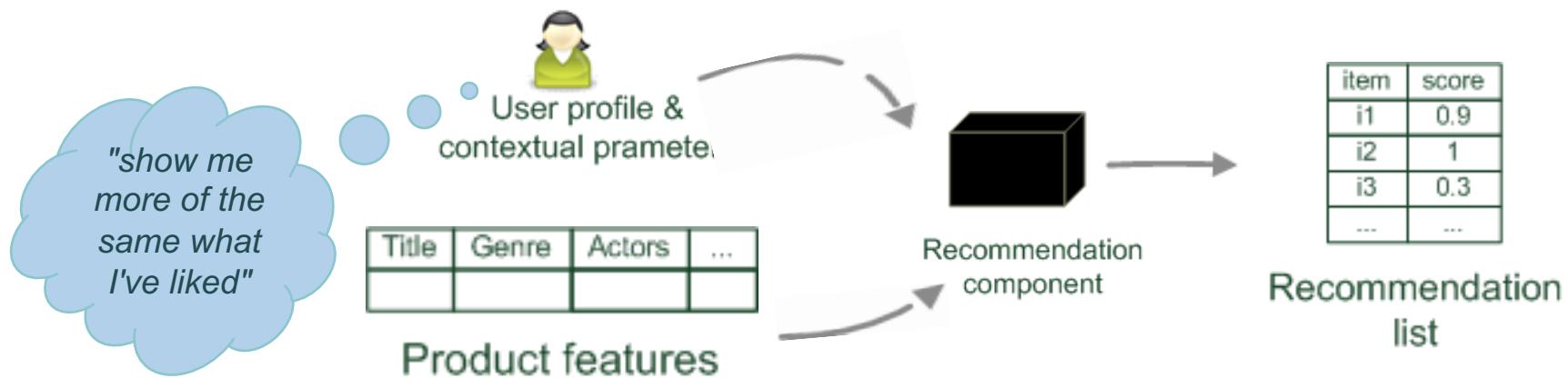
# An overview of Content-based Recommenders



- Based on the conjecture that a person likes items with features similar to those of other items she liked in the past
- Closely related to **Information Retrieval**
- Items are suggested according to:
  - A comparison between their content and the user profiles
- A **user profile** contains information about the user' tastes, interests and needs

# Content-based recommendation

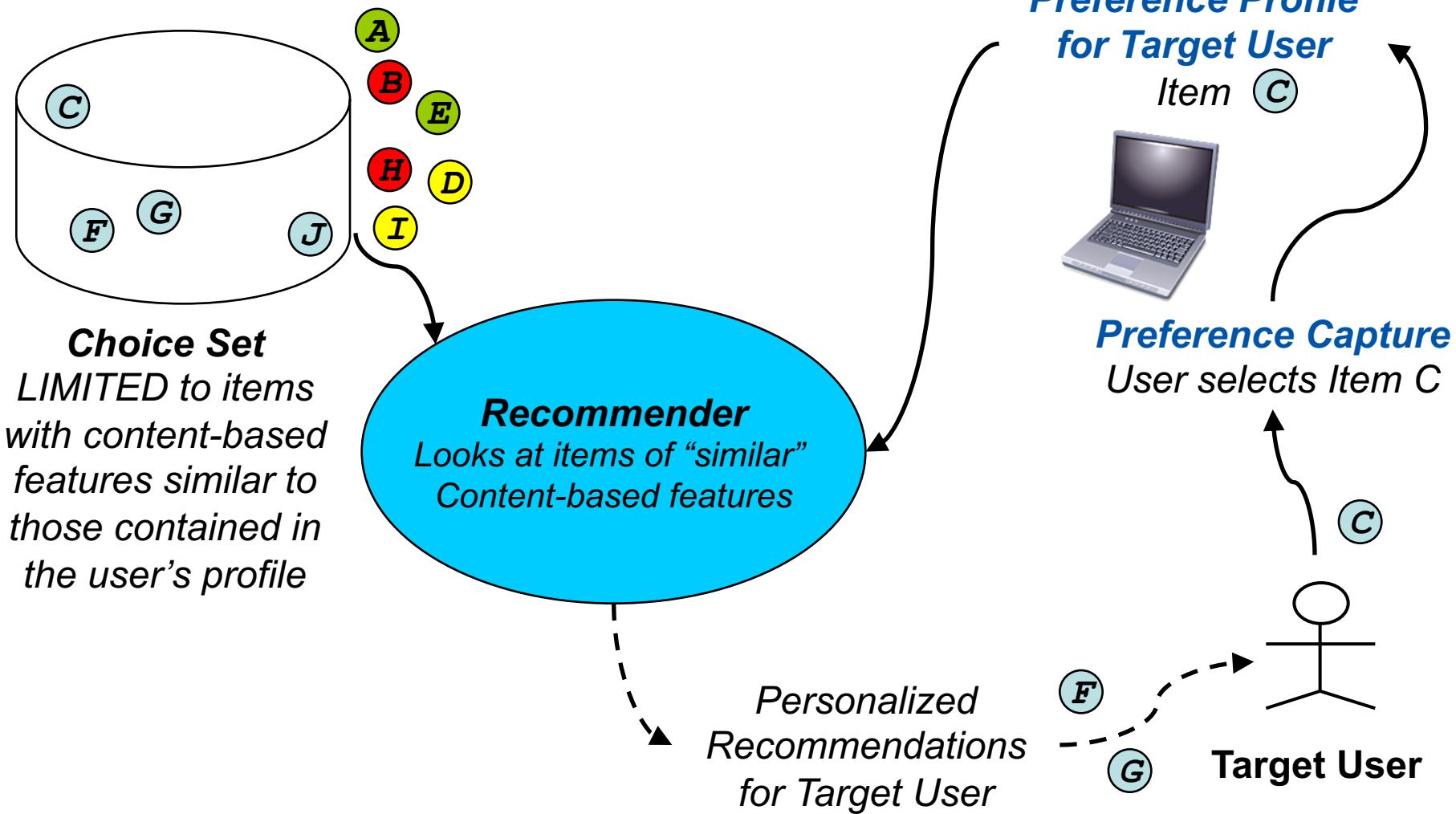
- **While CF – methods do not require any information about the items,**
  - it might be reasonable to exploit such information; and
  - recommend fantasy novels to people who liked fantasy novels in the past
- **What do we need:**
  - some information about the available items such as the genre ("content")
  - some sort of user profile describing what the user likes (the preferences)
- **The task:**
  - learn user preferences
  - locate/recommend items that are "similar" to the user preferences



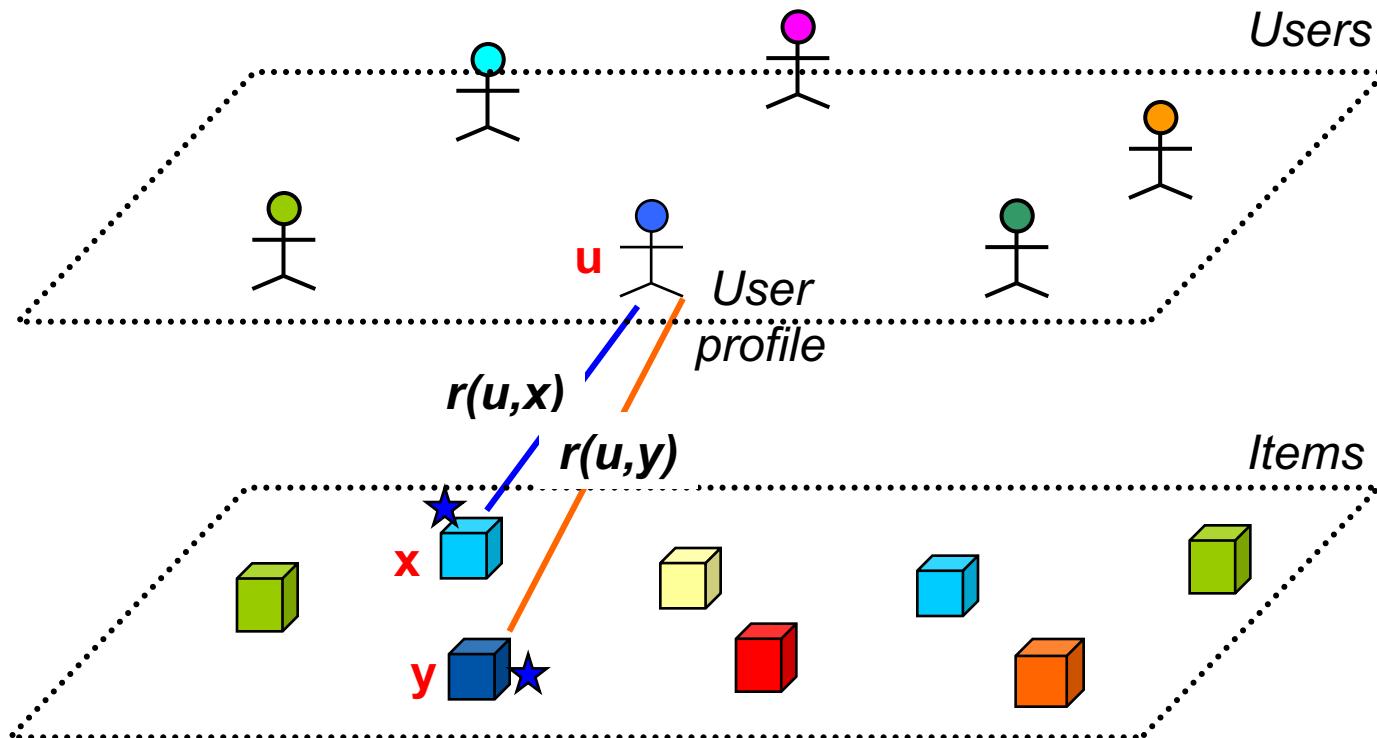
# Content-based recommenders

- **Content-based recommendation** systems share in common a means for:
  - Describing the items that may be recommended
  - Creating a profile of the user that describes the types of items the user likes
  - Comparing items to the user profile to determine what to recommend
- The profile is often created and updated automatically in response to **feedback** on the desirability of items that have been presented to her

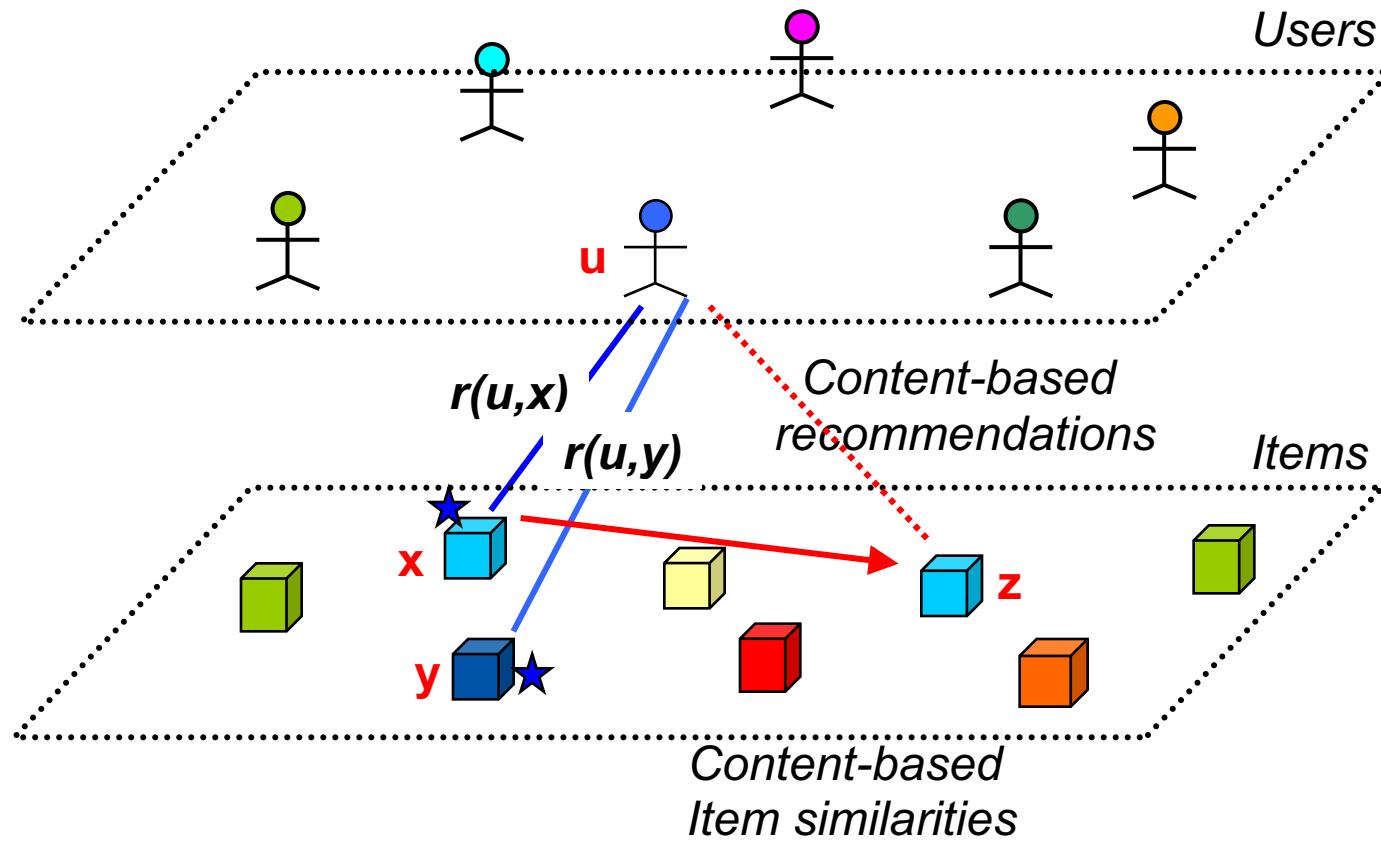
# Content-based



# Content-based



# Content-based



# Definition

- **Content-based recommendation** systems analyze item descriptions to identify items that are of particular interest to the user
- Items are suggested according to a comparison between their content and user profiles, which contain information about the users' tastes, interests and needs
- Most systems differ in the representation of items and how they get the feedback from users

# Representation of items

Called attributes, features, characteristics, fields or variables

- **Database table**



<b>Id</b>	<b>Name</b>	<b>Cuisine</b>	<b>Service</b>	<b>Cost</b>
10001	Bella Italia	Italian	Counter	Low
10002	Amour	French	Table	Medium
10003	Jacques Bistro	French	Table	High

- Attributes names with well-defined values
- **Unstructured data**, unrestricted text such as news, articles
  - There are no attribute names with well-defined values
- **Semi-structured data**
  - Some attributes with a set of restricted values and
  - Some free-text fields

# User profiles

- A profile of the user's interest is used by most recommendation systems
- **Types of information in a profile:**
  - A model of the **user's preferences**, a description of the types of items that interest the user
  - A **history of the user's interactions** with the recommendation system. This includes:
    - Storing the items that the user has viewed and
    - Other information about the user's interaction



Learn a user model

# Learning a user model

- Creating a user model of the user's preference from the user history is a form of classification learning
- **Explicit feedback**, the user rates items via some interface for collecting feedback
  - Few data but an accurate set of preferences
- **Implicit feedback**, the system observes the user's interactions with items
  - Can collect a large amount of data with some uncertainty as to whether the user actually likes the item

- **User independence**, no need for data on other users
  - No cold-start or sparsity problems
- **No grey sheep problem**, it is able to recommend to users with unique tastes
- **New item**, it is able to recommend new and unpopular items
  - No first-rater problem
- **Transparency**, can provide explanations of recommended items by listing content-features that caused an item to be recommended

- **Requires content analysis**, content that can be encoded as meaningful features
  - The effectiveness of the Rec depends on the available descriptive data
- Users' tastes must be represented as a learnable function of these content features
- **Content over-specialization**, it only retrieves items that score highly against a specific user profile
- **Portfolio-effect**, non diversity problem, the user should be presented with a diverse range of options, not with a homogeneous set of alternatives
- Unable to exploit quality judgments of other users
  - Unless these are somehow included in the content features

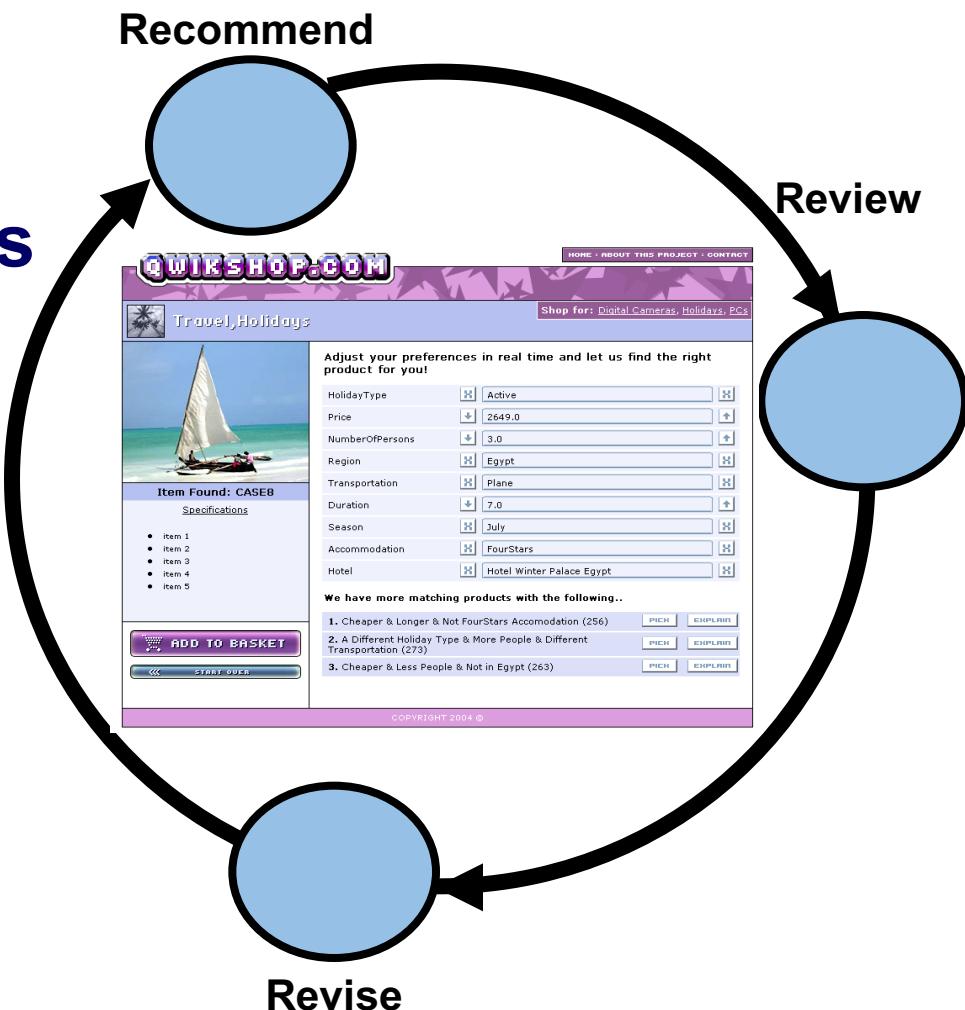


# Conversational Recommender Systems

## Conversational recommenders

(Jannach et al., 2020) guide the user through a complex problem space by alternatively making **suggestions** and using **user feedback** to influence future suggestions.

One way to provide **feedback** is based on **critiquing elicitation**  
(Chen and Pu, 2012)



- **Items are retrieved using similarity measures**
- Distance similarity

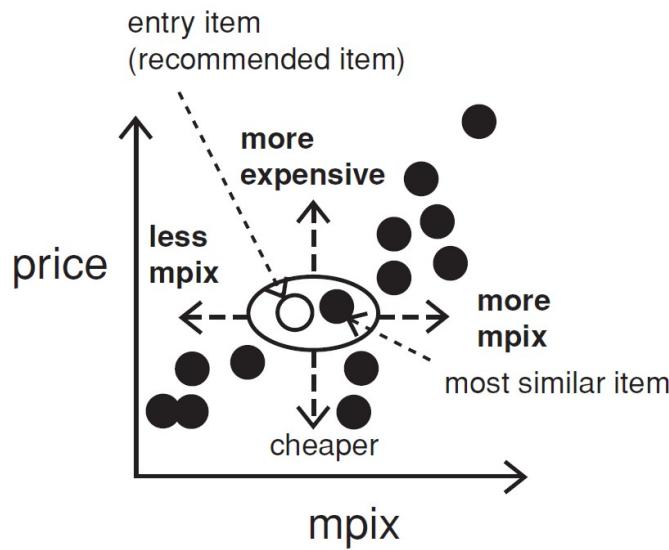
$$\text{similarity}(p, \text{REQ}) = \frac{\sum_{r \in \text{REQ}} w_r * \text{sim}(p, r)}{\sum_{r \in \text{REQ}} w_r}$$

- similarity (p, r) expresses for each item attribute value  $\varphi r$  (p) its distance to the customer requirement  $r \in \text{REQ}$ .
- $w_r$  is the importance weight for requirement r
- In real world, customer would like to:
  - maximize certain properties. i.e. resolution of a camera, "more is better" (MIB)
  - minimize certain properties. i.e. price of a camera, "less is better" (LIB)

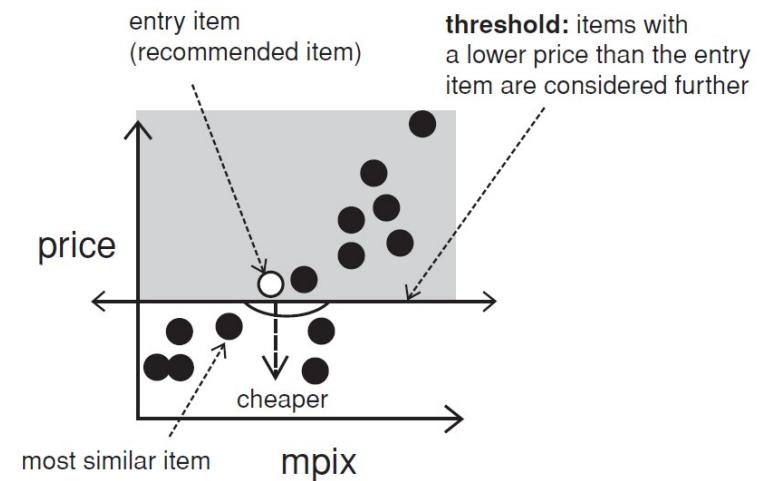
# Forms of feedback

- **Value elicitation**, approaches ask the user to provide details relating to specific features
- **Preference-based feedback and Rating-based**,
  - ask the user to indicate which product they prefer when presented with a small set of alternatives
  - to provide ratings for these alternatives
- **Critiquing or tweaking**, the user expresses a directional preference over the value-space for a particular product feature

- Customers maybe not know what they are seeking
- Critiquing is an effective way to support such navigations
- Customers specify their change requests (*price or mpix*) that are not satisfied by the current item (*entry item*)



*Critique on price*



# The Critiquing Approach

- **“FindMe Systems”**
  - Robin Burke [DePaul University], Kris Hammond [Northwestern University]
  - Previously of Computer Science Department of the University of Chicago.
  - Use CBR as a way of recommending products in e-commerce catalogs and provide critique-based navigation as a primary user interface.
- **Basic Assumption**
  - User has some product requirement.
  - Requirement is sufficiently vague (user cannot simply list all of the features).
  - User provides some initial features.
  - User is helped to locate a good product by critiquing additional features from intermediate recommendations.
  - Recommendations help influence the user's elaborate their initial query.
- **Practical Applications**
  - Restaurants, cars, cameras, property etc.

# An Example – “Find Me” Systems



*I would like to eat at a restaurant that has:*

Cuisine      Price  
Style      Atmosphere      Occasion

*I would like to eat at a restaurant just like:*

Chinois on Main      Los Angeles

New Query      Submit

Figure 1: Entry point for the Entree system

- **Entrée – A Restaurant Recommender System**
  - Users start off by indicating what kind of a restaurant they are looking for.
  - The system retrieves restaurants that are considered to be **similar** to the user's current requirements.

# Retrieval and User Feedback in Entrée

**Entrée Results**

**The Chicago restaurant you chose is:**

**Michael Jordan's**  
 500 N. LaSalle St. (Grand Ave. & Illinois St.), Chicago, 312-644-3865  
 American (New)      \$15-\$30  
 Excellent Decor, Good Service, Good Food, Business Scene, Hip Place To Be, Private Rooms Available, Private Parties, People Keep Coming Back, Parking/Valet, Great for People Watching, See the Game, Singles Scene, Pub Feel, Weekend Brunch

**We recommend:**

**Planet Hollywood** ([map](#))  
 638 N. Wells St. (Ohio St.), Chicago, 312-266-7827  
 American (New)      \$15-\$30  
 Excellent Decor, Good Service, Good Food, Traditional, Hip Place To Be, Private Rooms Available, Private Parties, No Reservations, Place for Singles, For the Young and Young at Heart, People Keep Coming Back, Late Night Menu, After Hours Dining, Parking/Valet, Great for People Watching, See the Game, Singles Scene, Pub Feel, Weekend Brunch, Tourist Appeal

**Unit Critique**

→ *less \$\$*   *nicer*   *cuisine*  
*traditional*   *creative*   *livelier*   *quieter*

- **User Feedback**

- The user indicates a feature critique or tweak to constrain the value range of that feature. E.g., Show me “more like this but cheaper”

- **Unit critiquing**
  - Express preference over a single feature
  - [ price, < , 1500]
- **Compound critiquing**
  - Critique operates over multiple features
  - [ price, < , 1500] and [memory, >, 2]

# Critique-based feedback

**QWIKSHOP.COM**

HOME : ABOUT THIS PROJECT : CONTACT

Digital Cameras

Shop for: Digital Cameras, Holidays, PCs



Adjust your preferences in real time and let us find the right product for you!

Manufacturer	<input checked="" type="checkbox"/> Canon	<input checked="" type="checkbox"/>
Model	<input checked="" type="checkbox"/> EOS-300D	<input checked="" type="checkbox"/>
Price (\$)	<input type="button" value="▼"/> 871.0	<input type="button" value="▲"/>
Format	<input checked="" type="checkbox"/> SLR	<input checked="" type="checkbox"/>
Resolution (M Pixels)	<input type="button" value="▼"/> 6.29	<input type="button" value="▲"/>
Optical Zoom (X)	<input type="button" value="▼"/> 10.0	<input type="checkbox"/>
Digital Zoom (X)	<input type="checkbox"/> 0.0	<input type="button" value="▲"/>
Weight (grams)	<input type="button" value="▼"/> 645.0	<input type="button" value="▲"/>
Storage Type	<input checked="" type="checkbox"/> Compact Flash	<input checked="" type="checkbox"/>
Storage Included (MB)	<input type="checkbox"/> 0.0	<input type="button" value="▲"/>

**Item Found: CASE2**

Specifications

6.3 Megapixel CMOS sensor  
7-point wide-area AF  
High-performance DIGIC processor  
100-1600 ISO speed range  
Compatible with all Canon EF lenses and EX Speedlites  
PictBridge, Canon Direct Print and Bubble Jet Direct compatible – no PC required

 **ADD TO BASKET**

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**Unit Critiques**

# Critique-based feedback

## Unit Critiques

**QUIKSHOP.COM**

Travel, Holidays

Shop for: Digital Cameras, Holidays, PCs

Adjust your preferences in real time and let us find the right product for you!

HolidayType	Active	X
Price	2649.0	↑ ↓
NumberOfPersons	3.0	↑ ↓
Region	Egypt	X
Transportation	Plane	X
Duration	7.0	↑ ↓
Season	July	X
Accommodation	FourStars	X
Hotel	Hotel Winter Palace Egypt	X

We have more matching products with the following..

1. Cheaper & Longer & Not FourStars Accomodation (256) **PICK** **EXPLAIN**
2. A Different Holiday Type & More People & Different Transportation (273) **PICK** **EXPLAIN**
3. Cheaper & Less People & Not in Egypt (263) **PICK** **EXPLAIN**

**ADD TO BASKET**

**START OVER**

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The user indicates a directional feature preference in relation to a presented recommendation

# Critique-based feedback

## Unit Critiques

**QUIKSHOP.COM**

Travel, Holidays

Shop for: Digital Cameras, Holidays, PCs

Adjust your preferences in real time and let us find the right product for you!

HolidayType	Active	↑ ↓
Price	2158.0	↑ ↓
NumberOfPersons	2.0	↑ ↓
Region	Corfu	✗
Transportation	Plane	✗
Duration	7.0	↑ ↓
Season	July	✗
Accommodation	FourStars	✗
Hotel	Hotel Regency Corfu	✗

We have more matching products with the following..

- Different Transportation & Longer & Not FourStars Accommodation (239) PICK EXPLAIN
- A Different Holiday Type & More People & Not in July (379) PICK EXPLAIN
- Longer & Not in the Hotel Regency Corfu (490) PICK EXPLAIN

**ADD TO BASKET**

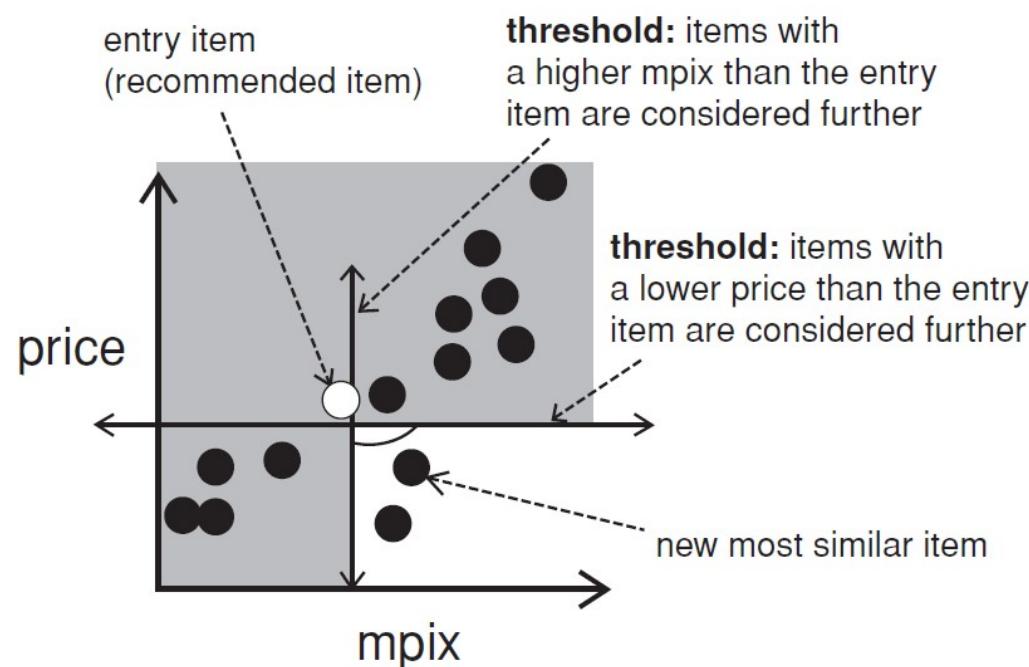
« START OVER

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The traditional implementation of critiquing can lead to protracted recommendation sessions as there is a tendency towards relatively minor changes in the values of critiqued features from cycle to cycle

# Compound critiques

- Operate over multiple properties can improve the efficiency of recommendation dialogs





# Dynamic Critiquing

**QUIKSHOP.COM**

HOME : ABOUT THIS PROJECT : CONTACT

Digital Cameras

Shop for: Digital Cameras, Holidays, PCs



Adjust your preferences in real time and let us find the right product for you!

Manufacturer	<input checked="" type="checkbox"/> Canon	<input type="checkbox"/>
Model	<input checked="" type="checkbox"/> EOS-300D	<input type="checkbox"/>
Price (\$)	<input type="button" value="↓"/> 871.0	<input type="button" value="↑"/>
Format	<input checked="" type="checkbox"/> SLR	<input type="checkbox"/>
Resolution (M Pixels)	<input type="button" value="↓"/> 6.29	<input type="button" value="↑"/>
Optical Zoom (X)	<input type="button" value="↓"/> 10.0	<input type="checkbox"/>
Digital Zoom (X)	<input type="checkbox"/> 0.0	<input type="button" value="↑"/>
Weight (grams)	<input type="button" value="↓"/> 645.0	<input type="button" value="↑"/>
Storage Type	<input checked="" type="checkbox"/> Compact Flash	<input type="checkbox"/>
Storage Included (MB)	<input type="checkbox"/> 0.0	<input type="button" value="↑"/>

**Item Found: CASE2**

**Specifications**

6.3 Megapixel CMOS sensor  
7-point wide-area AF  
High-performance DIGIC processor  
100-1600 ISO speed range  
Compatible with all Canon EF lenses and EX Speedlites  
PictBridge, Canon Direct Print and Bubble Jet Direct compatible - no PC required

**ADD TO BASKET**

**START OVER**

We have more matching products with the following..

1. Less Optical Zoom & More Digital Zoom & A Different Storage Type (139) **PICK** **EXPLAIN**
2. A Lower Resolution & A Different Format & Cheaper (169) **PICK** **EXPLAIN**
3. A Different Manufacturer & Less Optical Zoom & More Storage (167) **PICK** **EXPLAIN**

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**Unit Critiques**

**Compound Critiques**

# Explanatory Benefits

Storage Included (MB)  32.0

**We have more matching products with the following..**

- 1.** A Different Manufacturer & A Lower Resolution & Cheaper (67)
- 2.** A Different Format & Less Digital Zoom & Less Optical Zoom (60)
- 3.** A Different Model & Heavier & More Expensive (54)

The Compound Critique you have chosen is:  
**A Different Manufacturer & A Lower Resolution & Cheaper**

This critique covers **67** cases in the casebase.

**Explanation:**

**Manufacturer**  
- Value = Sony,  
- Critique = Not Equal To Nominal ('<>')  
- Range Remaining =  
(Nikon, Kodak, Canon, Ricoh, Fuji, Pentax, Toshiba, Samsung, Olympus, Konica Minolta, Casio, Contax, Hewlett-Packard, Kyocera)

**Resolution**  
- Value = 5.0  
- Critique = Less Than Ordinal ('<')  
- Range Remaining =  
(1.9 to 4.92)

**Price (\$)**  
- Value = 289.0,  
- Critique = Greater Than Ordinal ('>')  
- Range Remaining =  
(292.0 to 7439.0)

 Done  Internet

# Diversity Enhancement

1. A Different Manufacturer & Less Pixels & Cheaper (72)

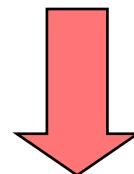
PICK

2. Less Pixels & Less Memory & Cheaper (84)

PICK

3. A Different Type of Memory & Different Software & Cheaper (80)

PICK



1. A Different Manufacturer & Less Pixels & Cheaper (72)

PICK

2. A Different Model & More Memory & More Expensive (79)

PICK

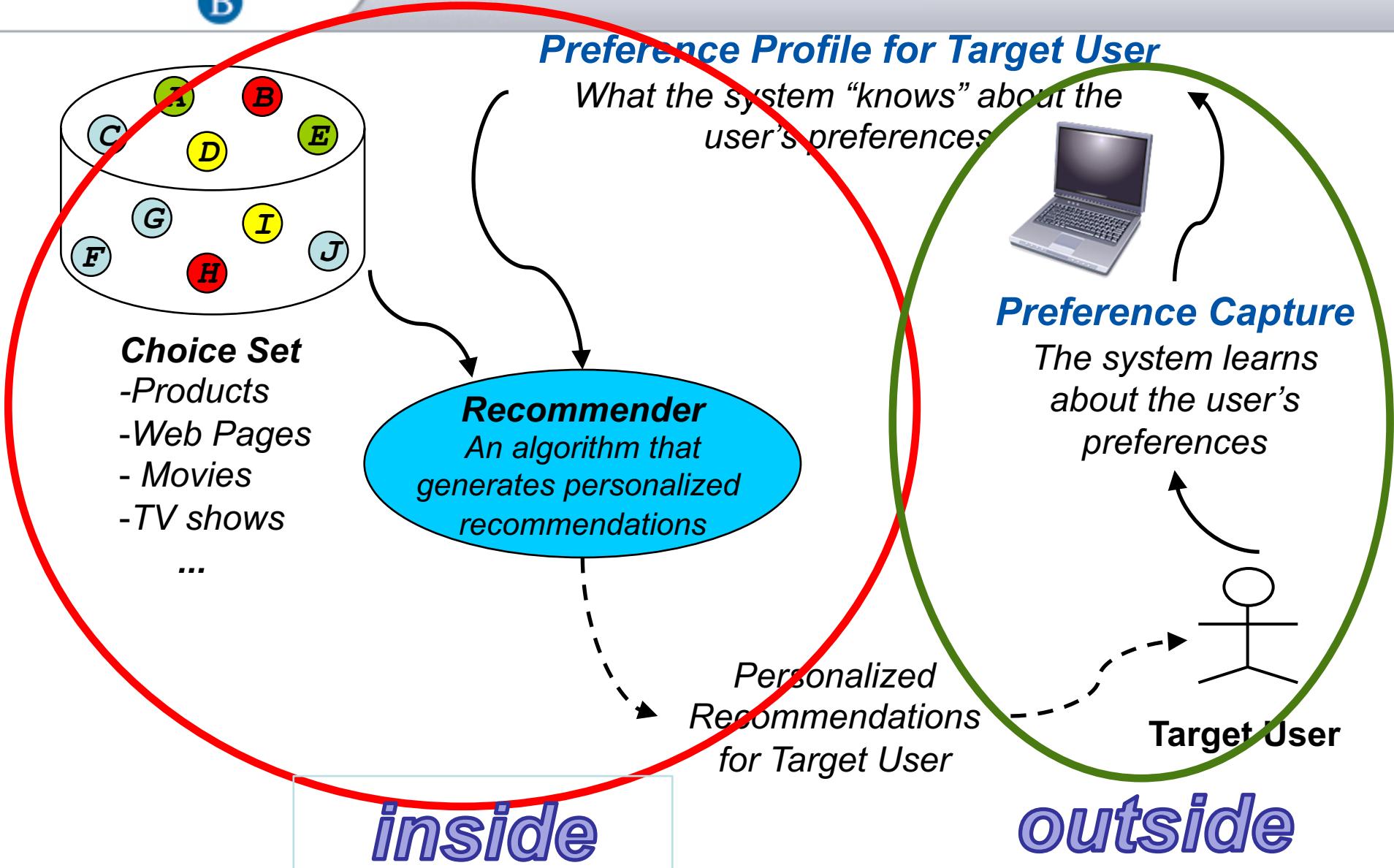
3. A Different Type of Memory & Different Cable & Less Memory (83)

PICK

- **Advantages**
  - No ratings are necessary
  - Avoid cold start problem
- **Limitations**
  - cost of knowledge acquisition
    - from domain experts
    - from users
    - from web resources
  - accuracy of preference models
    - very fine granular preference models require many interaction cycles

# Outside Recommender Systems

# Components of a recommender



- **Recommenders need an interface for capturing user's interactions**
- **The interface is the key component** for obtaining user's preferences and it is designed based on:
  - The type of recommender
  - The type of preferences that should be collected for the user profiles
- Common taxonomy of interfaces:
  - 2D interfaces
  - Mobile interfaces
  - 3D Interfaces



## Conversational Recommender Systems

- ❑ Recommenders and its interaction to 2D (web-based) and 3D interfaces (Virtual Worlds)
- ❑ Recommenders and natural language interaction with assistants
- ❑ Single Recommenders
- ❑ Group Recommenders



# Outside Conversational Recommender Systems

1. 3D Virtual Worlds
2. Cognitive Assistants
3. gCoach: Collaborative Group Recommender

# 3D Virtual Worlds and Recommenders

- Contreras, D., Salamó, M., Rodríguez, I., Puig, A. ***Shopping Decisions Made in a Virtual World: Defining a State-Based Model of Collaborative and Conversational User-Recommender Interactions***, Journal IEEE Consumer Electronics Magazine, 7(4), pp. 26-35 (2018), [doi: 10.1109/MCE.2017.2728819](https://doi.org/10.1109/MCE.2017.2728819)
- Contreras, D., Salamó, M., Rodríguez, I., Puig, A. ***A 3D Visual Interface for Critiquing-based Recommenders: Architecture and Interaction***. Journal IJIMAI 3 (3): pp. 7-15 (2015)



# Goal in 3D Virtual Conv. Rec

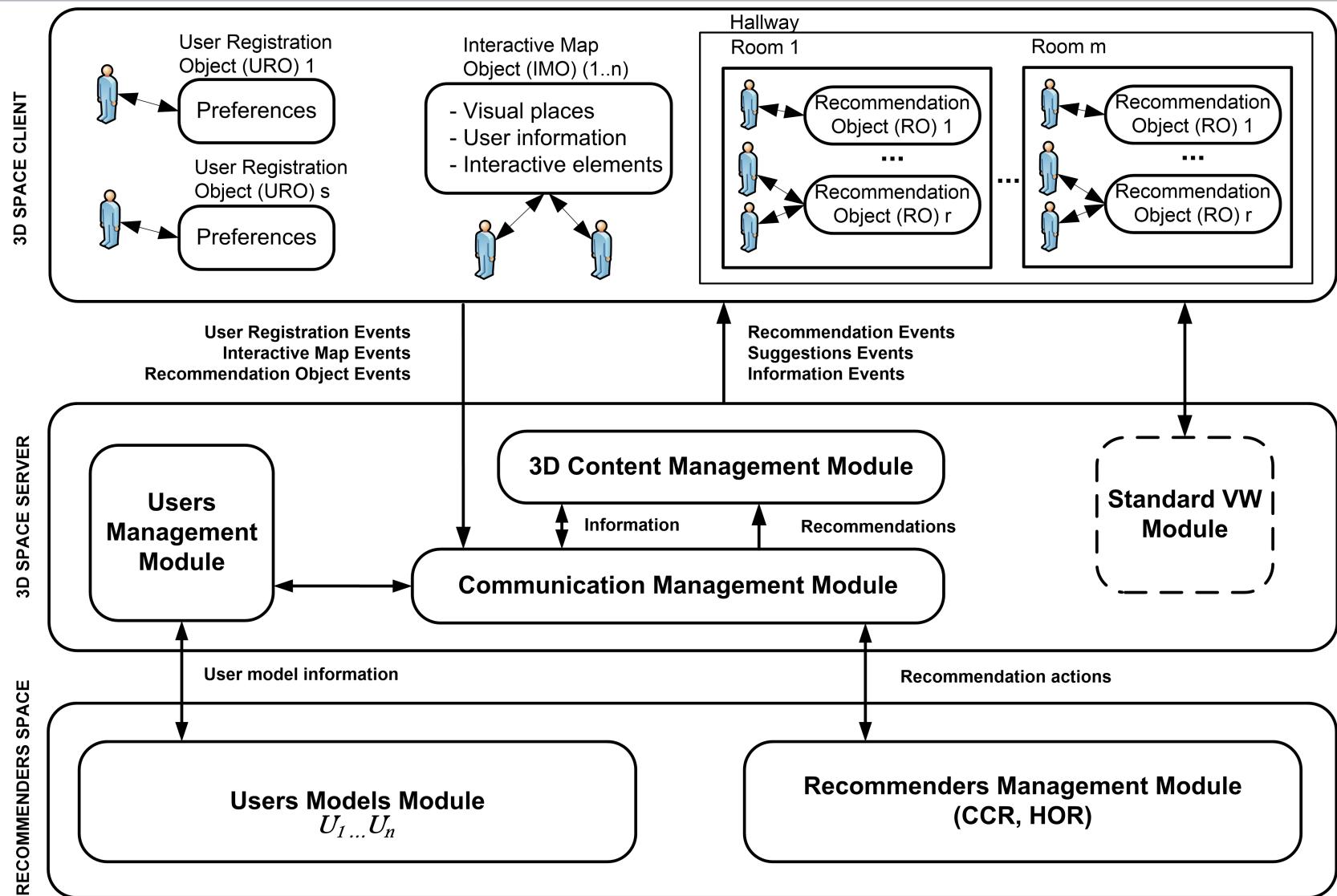


Design a SCALABLE framework to enhance and facilitate user buying experience in a large 3D eCommerce space



(OPTIONAL) <https://youtu.be/jX91kSnmQn8>

# Framework 3D VW and Conv. Rec



## User Registration Object (URO)

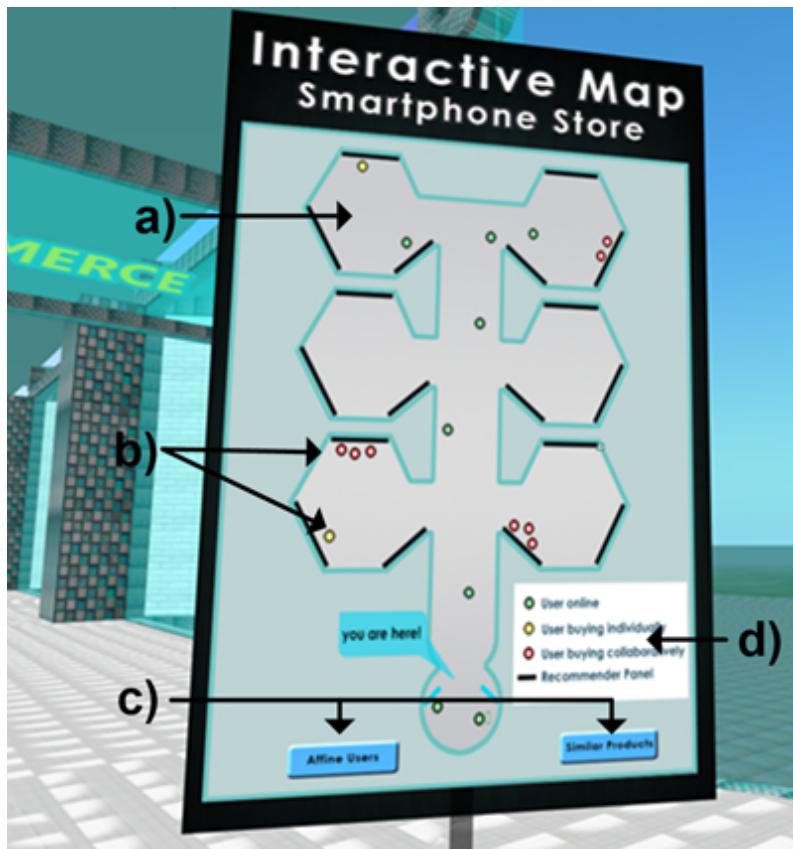


- URO allows users register their initial preferences when they arrive to 3D eCommerce Space.
- Later, the system provides the users with recommendations based on these preferences.
- It complements the conversational recommendation process.

In the figure are shown the following preferences:

- mobile phone operating system and price, in the Smartphone domain

## Interactive Map Object (IMO)



The user can:

- a) See all rooms in the eCommerce space,
- b) Know which other users are interacting with Recommendation Objects (RO).
- c) Ask for suggestions about rooms where they should go to find the users or products that matches their preferences.

# Interaction Objects (III)

## Recommendation Object (RO)

	<b>Manufacturer</b> Sony	<b>RAM</b> 3 GB RAM
	<b>Model</b> Xperia Z2	 2.3 GHz Qualcomm
	<b>Price</b> \$599.00	 20.7 MP
	<b>Weight</b> 163 g	 Android 4.4
	<b>Size</b> 5.2"	 1/2.3" sensor size touch focus
<b>Description</b> Manufacturer: Sony Model: Xperia Z2 O.S.: Android 4.4		

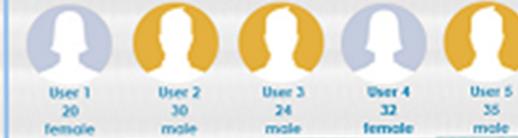
Based on User Preferences and History recommendations

### Suggestions

Are you interested in?



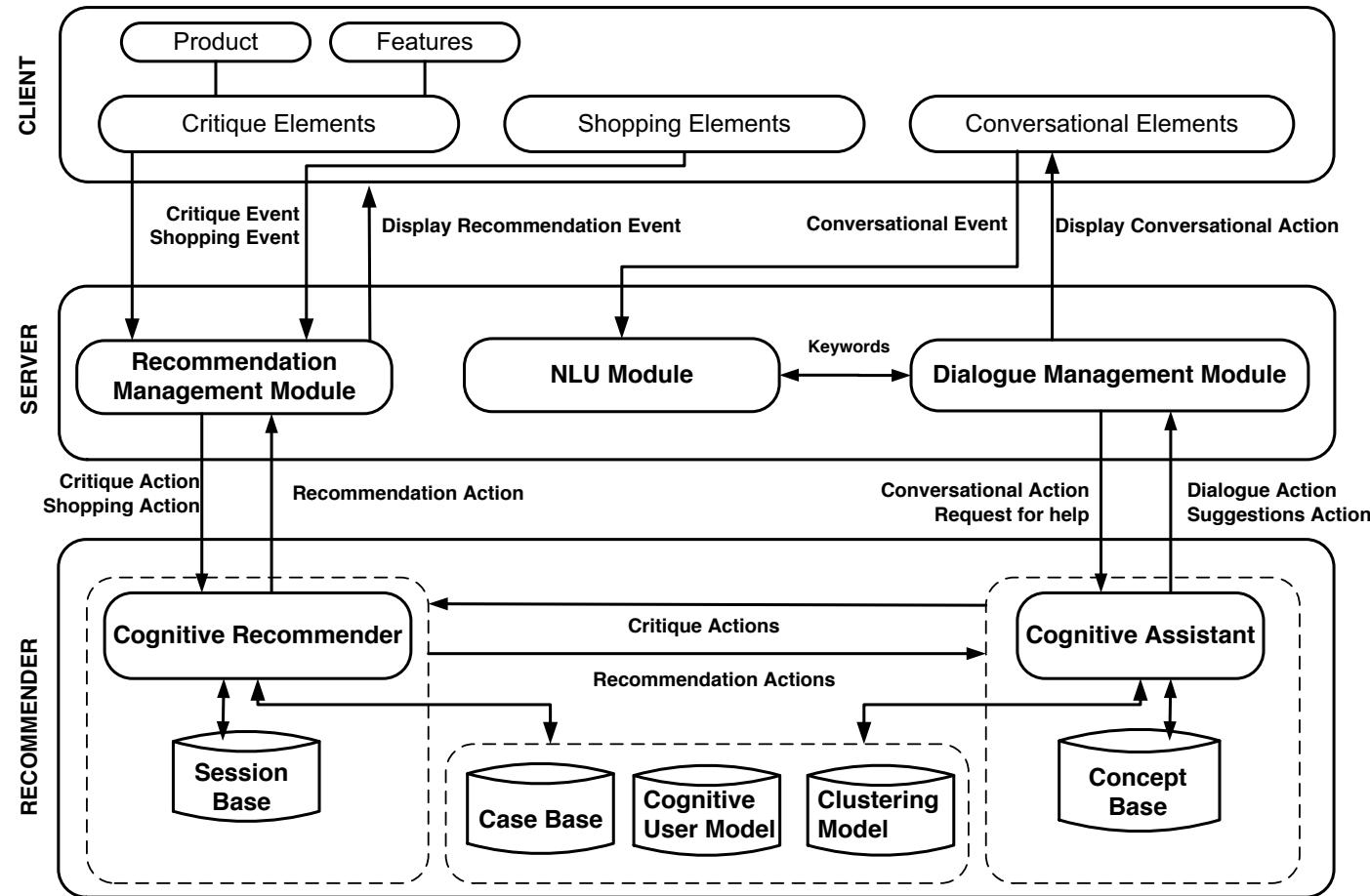
Like you collaborate?



# Cognitive Assistant

Güell, M., Salamó, M., Contreras, D., Boratto, L. **Integrating a cognitive assistant within a critique-based recommender system.** Journal Cognitive Systems Research, Volume 64, pp. 1-14, (2020), <https://doi.org/10.1016/j.cogsys.2020.07.003>

# Conceptual Architecture



# User Interface

### Recomendación / Recommendation



### Objetivo / Target



Manufacturer: HTC  
Model: DROIDIncredible2  
Weight: 135.00 gr  
Size: 4.00 "  
Storage: 1.10 Mb  
Ram: 768.00 Mb  
CAM: 8.00 Mpixels  
O.S.: Android OS, v2.2 (Froyo), upgradable to v4.0 (Ice Cream Sandwich)  
CPU: 1 GHz Scorpion  
Price: 220.00 euro

Manufacturer	Model	Weight	Size
Huawei	AscendY300	130.00 gr	4.00 "
Storage	Ram	CAM	O.S.
4.00 Mb	512.00 Mb	5.00 Mpixels	Android OS, v4.1 (Jelly Bean)
CPU	Price		
Dual-core 1 GHz Cortex-A5	90.00 euro		

ChatBot    Reset

¿Qué atributos deseas modificar del móvil actual? o escribe help para que te haga una sugerencia.

otro fabricante y mas precio

¡Perfecto! voy a tener en cuenta tu opinión para el siguiente móvil

¿Qué atributos deseas modificar del móvil actual? o escribe help para que te haga una sugerencia.

otro fabricante y mas precio

¡Perfecto! voy a tener en cuenta tu opinión para el siguiente móvil

¿Qué atributos deseas modificar del móvil actual? o escribe help para que te haga una sugerencia.

otro fabricante y mas precio

¡Perfecto! voy a tener en cuenta tu opinión para el siguiente móvil

¿Qué atributos deseas modificar del móvil actual? o escribe help para que te haga una sugerencia.

Escribe algo...



(OPTIONAL) <https://youtu.be/JRuFRXku4Qw>

Derechos reservados por 2DCommerce

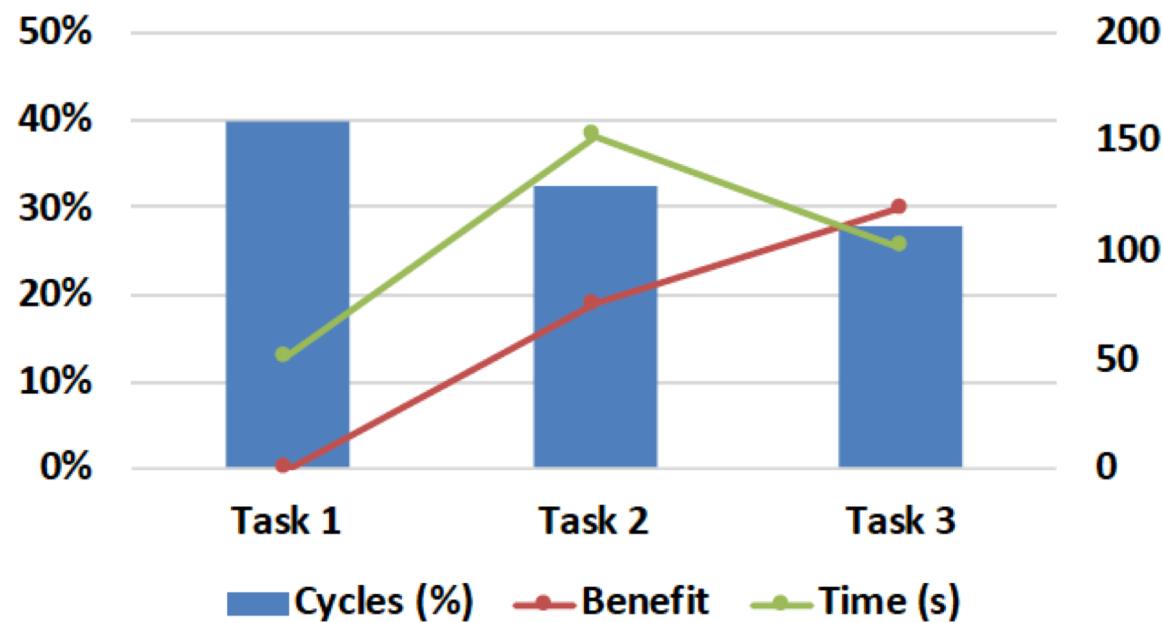
# Results: Efficiency

**Task 1.** Only buttons

**Task 2.** Only the assistant

**Task 3.** Both buttons and assistant

**Between subject test**  
**40 users**



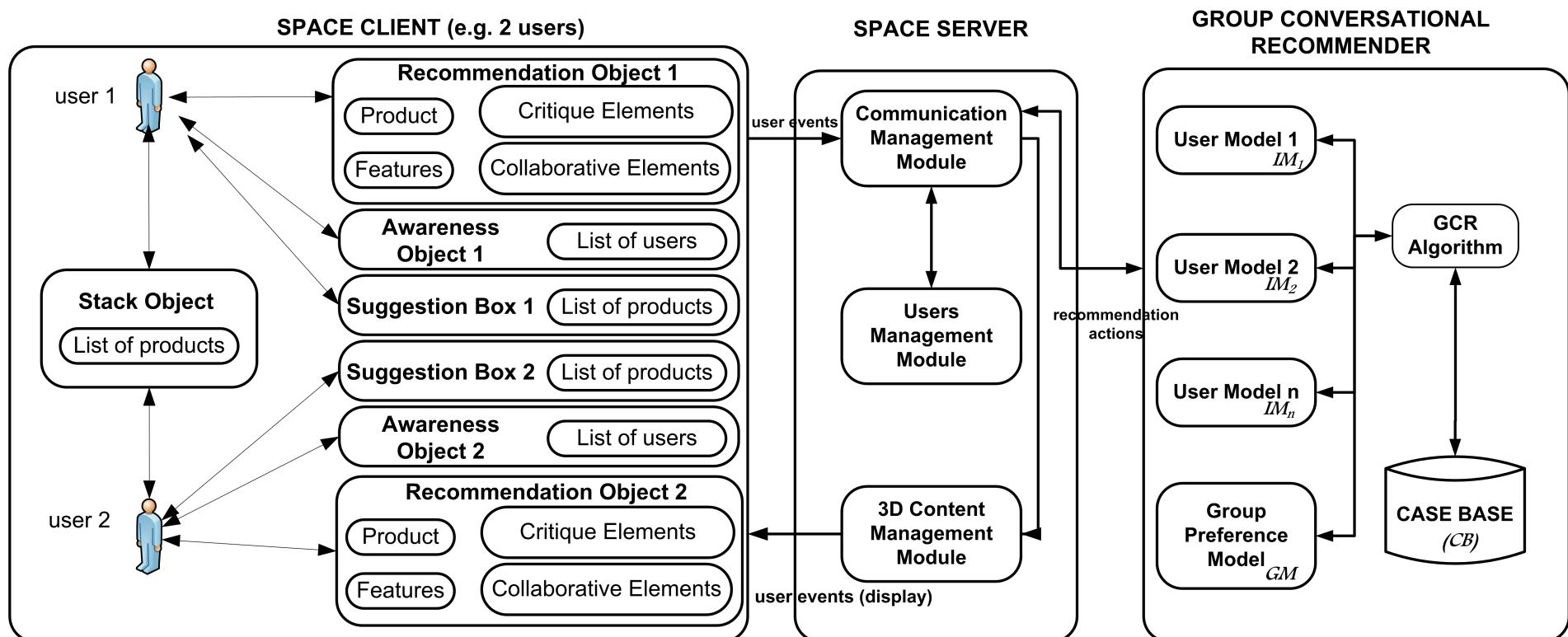
**Smartphone dataset**

# gCoach for online Group Recommendation

Contreras, D., Salamó, M., Pascual, J. *A Web-Based Environment to Support Online and Collaborative Group Recommendation Scenarios*. Applied Artificial Intelligence. pp 480-499 (2015)

- **gCOACH: Collaborative Advisory Channel for group recommendations**
- **Novel web-based environment** that supports on-line group recommendation
  - **Synchronizes all the actions** of users
  - Contains **multiple interaction modalities** to communicate, coordinate and persuade the group
- Conversational case-based group recommender

# gCOACH conceptual architecture



# gCOACH interaction modalities

Your Color

User: Red

**FINISH SESSION**

To finish session when reached a product that satisfies the user

5

Hotel Delle Alpi  
Passo Tonale  
Standard Hotel  
  
529.0 €  


Hotel Orlovetz  
Pamporovo  
Luxury Hotel  
  
609.0 €  


Livigno Ski Apartments  
Livigno  
Residence CybÈle  
Meribel Valley  
Apartment  
  
329.0 €  


Hotel Eggerwirt  
Soll  
Standard Hotel  
  
599.0 €  


La Riviere  
Chamonix

## Hotel Garni St Georg



Accommodation:	Standard Hotel	X
Price:	419.0 €	
Restaurant:	NO	X
Bar-Lounge:	NO	X
Car Park:	NO	X
Children's playroom:	NO	X
Cot:	NO	X
Ensuite Bath :	YES	X
Ski Room:	YES	X
Health Facilities:	NO	X
Swimming pool:	YES	X
Hair Dryier :	NO	X
Balcony Rooms:	YES	X
Sauna:	YES	X
Safety Deposit Box:	NO	X
Fitness room:	YES	X



ResortLocation:	Austria
ResortName:	Seefeld
Beginner:	
Intermediate:	
Advanced:	
Snowboard:	★
Black:	2.0
Red:	8.0
Blue:	8.0
Green:	0.0
LongestPista:	4.0
TotalKM:	23.0
Cannons:	72.0
Transfer Time:	0.5
Chair Lifts:	4.0
Drag Lifts:	18.0
Gondola:	2.0
Cable Car:	0.0
CrossCountry:	YES
Floodlit skiing:	NO
HalfPipe:	YES
Ice Skating:	NO
Tobogganing:	YES

BACK

1

Numeric Critique

Nominal Critique

2

User: Red

Actual Hotel: Actual compatibility



User: Blue

Actual Hotel: Actual compatibility



User: Green

Actual Hotel: Actual compatibility



User: Yellow

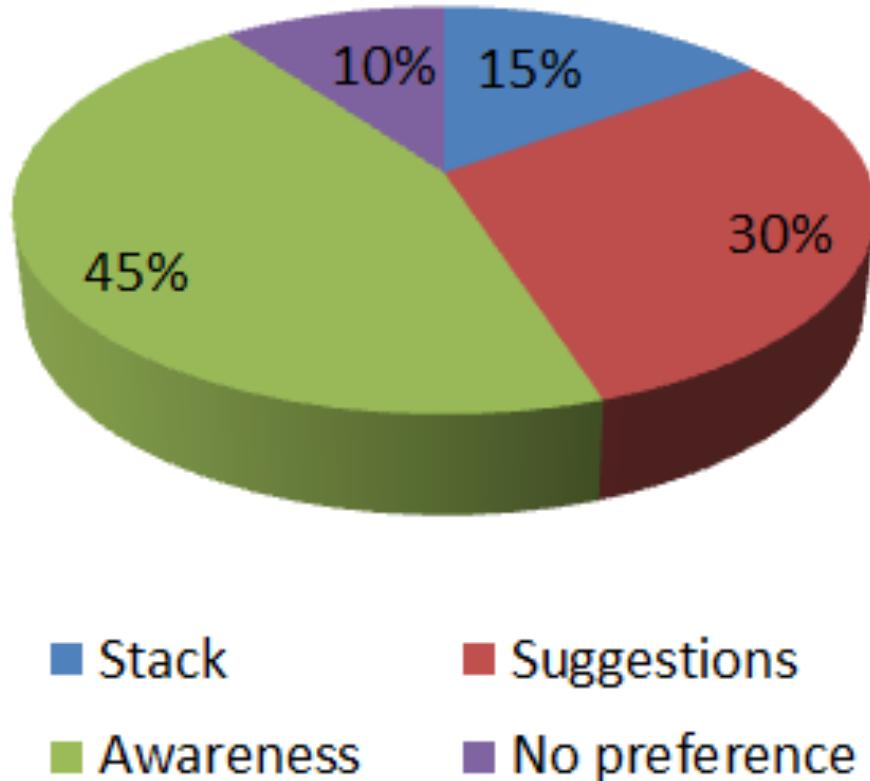
Actual Hotel: Actual compatibility



3



# Results: Usability Evaluation



*The majority of the users prefer the “Awareness Area”*

# What else?



## TO READ:

An Introduction to Recommender Systems

Aggarwal, C.C.

**Sections 1.1, 1.2, 1.3**

Sections 1.4, 1.5, 1.6 and 1.7 are optional



***Look at the video (OPTIONAL)***

*Recommender Systems: Beyond Machine Learning*  
*Joseph A. Konstan*

<https://youtu.be/uupJmZG5xxA>

*From minute 5:30 to the end*

## Week 11

# Course. Introduction to Machine Learning **Theory 11. Recommender Systems**

Dr. Maria Salamó Llorente  
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Faculty of Mathematics and Informatics,  
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