Recommender Systems

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Content

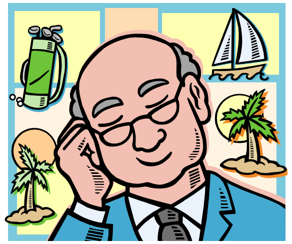
- The paradox of choice and information overload
- Personalization
- Recommender systems
- Step 1: preference elicitation
- Step 2: preference prediction - rating estimation techniques
  - Contextualization
  - Groups
- Step 3: recommendations' presentation
- Issues and problems

Explosion of Choice

- A trip to a **local supermarket**:
  - 85 different varieties and brands of crackers
  - 285 varieties of cookies.
  - 165 varieties of “juice drinks”
  - 75 iced teas
  - 275 varieties of cereal
  - 120 different pasta sauces
  - 80 different pain relievers
  - 40 options for toothpaste
  - 95 varieties of snacks (chips, pretzels, etc.)
  - 61 varieties of sun tan oil and sunblock
  - 360 types of shampoo, conditioner, gel, and mousse.
  - 90 different cold remedies and decongestants.
  - 230 soups, including 29 different chicken soups
  - 175 different salad dressings and if none of them suited, 15 extra-virgin olive oils and 42 vinegars and make one’s own

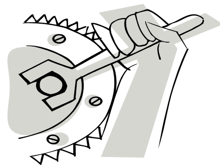
New Domains for Choice

- Telephone Services



- Retirement Pensions
- Medical Care

- News
- Choosing how to work



- Choosing how to love

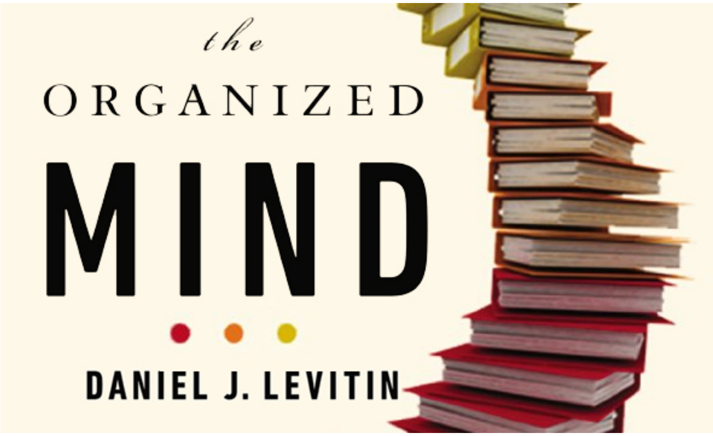
- Choosing how to be

Choice and Well-Being

- We have **more choice**, more freedom, autonomy, and self determination
- Increased choice ***should*** **improve well-being:**
  - *added options can only make us better off: those who care will benefit, and those who do not care can always ignore the added options*
- Various assessment of well-being have shown that **increased affluence** have accompanied by **decreased well-being**.

Neuroscience and Information Overload

- Neuroscientists have discovered that unproductivity and loss of drive can result from **decision overload**
- Our brains (**120 bits per second**) are configured to make **a certain number of decisions per day** and once we reach that limit, we can't make any more
- **After the limit is reached** we can have trouble separating the trivial from the important.



Information Overload

- **Internet = information overload =** having too much information to **make a decision** or **remain informed about a topic**
- To make a decision or remain informed about a topic you must perform **exploratory search** (e.g., comparison, knowledge acquisition, product selection, etc.)
  - *not aware of the range of available options*
  - *may not know what to search*
  - *if presented with some results may not be able to choose.*

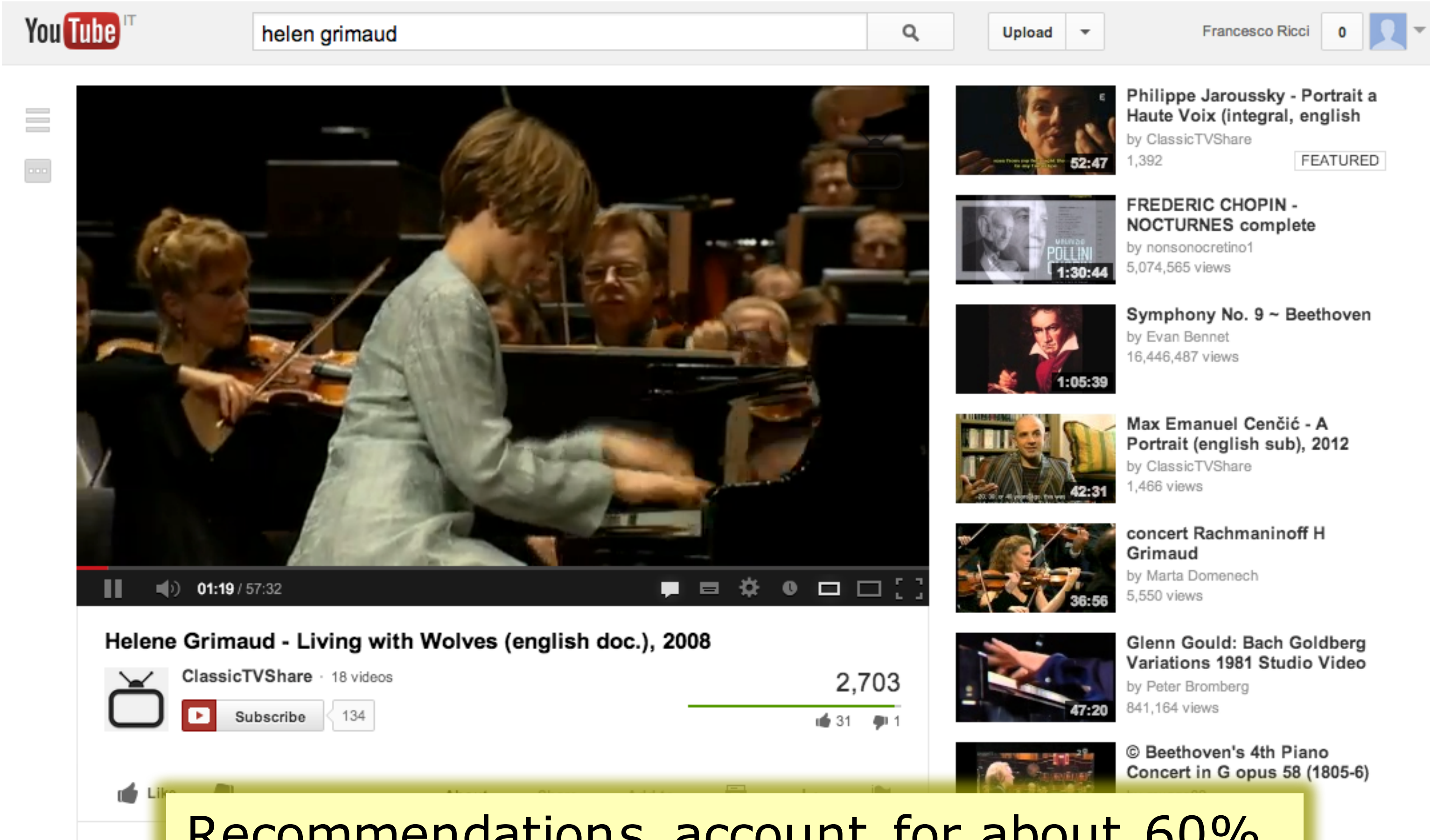
eCommerce Personalization

- *"If I have 3 million customers on the Web, I should have 3 million stores on the Web"*
  - **Jeff Bezos**, CEO and founder, Amazon.com
  - Degree in Computer Science
  - $34.2 billion (net worth), ranked no. 15 in the Forbes list of the America's Wealthiest People

Amazon.it


amazon.it Prime
Amazon.it di Ricci | Offerte | Buoni Regalo | Vendere | Aiuto
kindle paperwhite › 129€
Scegli per categoria
Ricerca
Tutte le categorie
VAI
Ciao Ricci
Il mio account
4
Carrello
Lista Desideri
Il mio Amazon.it
Consigliato in base alla cronologia di navigazione
Consigliati per te
Valuta questi articoli
Migliora i suggerimenti per te
Il mio profilo
Ulteriori informazioni
Ciao Ricci (Se non sei Ricci Francesco, clicca qui)
I suggerimenti di oggi
Ecco una selezione giornaliera degli articoli suggeriti. Clicca qui per visualizzare tutti i suggerimenti.
Pagina 1 di 44
1Q84. Libro 3. Ottobre-dicembre (Rilegato) di Haruki Murakami
(66) EUR 15,73
Migliora questo suggerimento
Martha Argerich & Friends - Li... (Audio CD) ~ Martha Argerich
(1) EUR 13,71
Migliora questo suggerimento
L'uccello che girava le viti... (Brossura) di Haruki Murakami
(8) EUR 13,13
Migliora questo suggerimento
A sud del confine, a ovest de... (Rilegato) di Haruki Murakami
(2) EUR 17,00
Migliora questo suggerimento

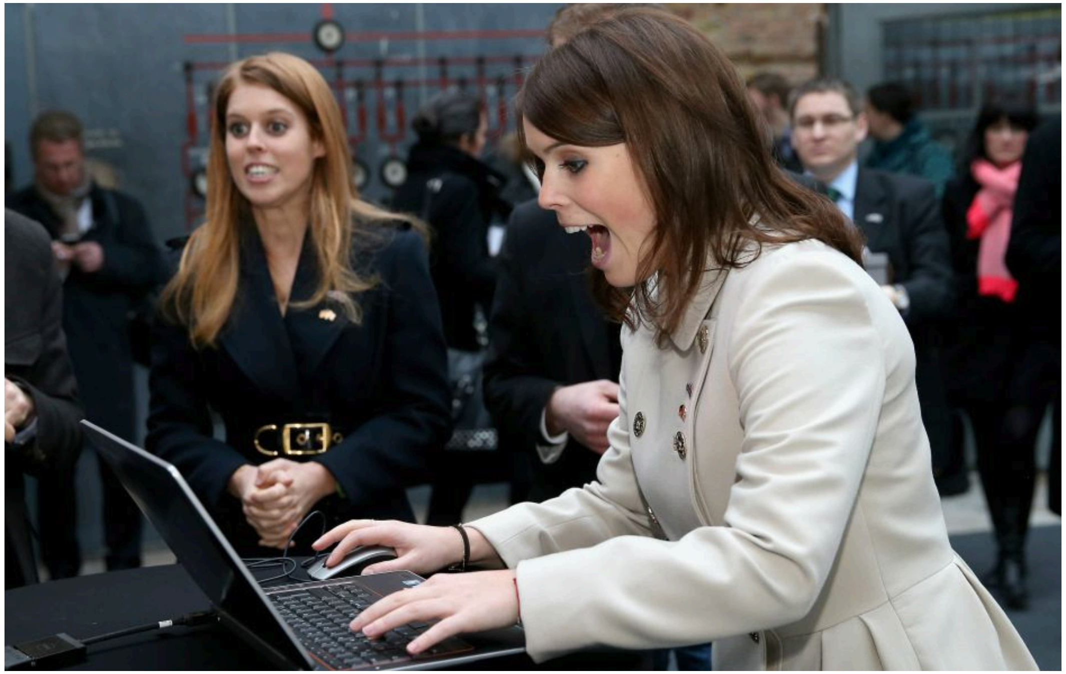
Movie Recommendation – YouTube



Recommendations account for about 60% of all video clicks from the home page.

Who is this company?

- *"Italians are emotional, the Swiss are punctual"*
- This shopping site is making billions by tailoring its services to European stereotypes



Zalando: Europe's largest dedicated online apparel retailer, with several thousand employees facilitating annual sales topping €2.2 billion.

http://qz.com/482553

Consumer Attitudes

Consumer Attitudes to Personalized Shopping Experiences

% of respondents

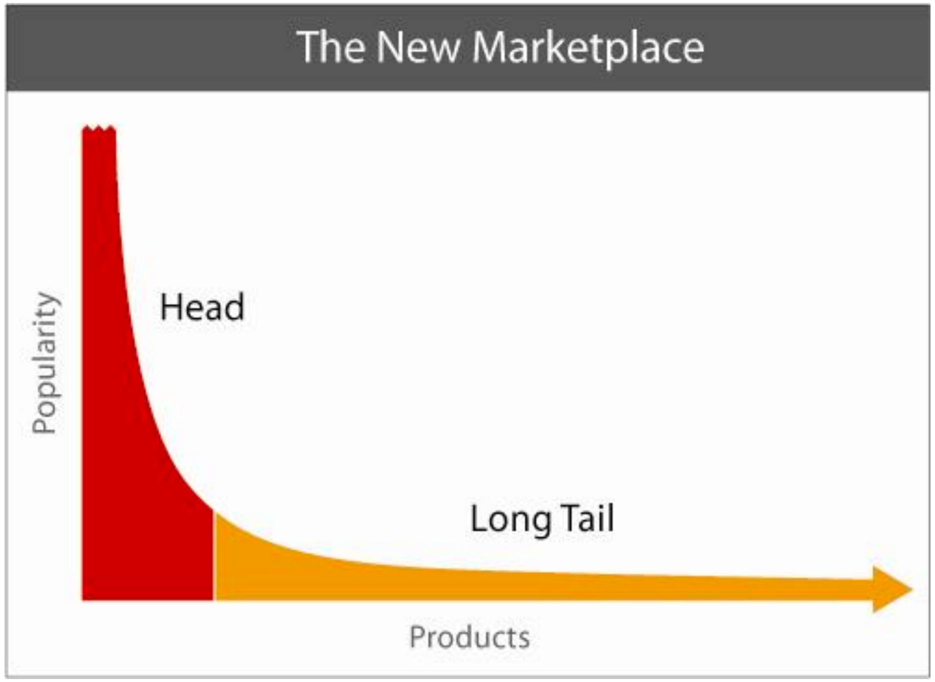
January 2014

20%	of respondents have encountered personalized offers/promotions in-store, while 27% have seen them online
32%	have experienced product recommendations bsaed on previous purchases online, compared to 18% in-store
86%	of those who have experienced personalization believe it has influenced what they purchase to some extent, including 25% who believe it has significantly influenced what they purchase
67%	of those who have experienced personalization are in favor of personalized coupons; personalized offers/promotions based on previous experiences (62%) and product recommendations based on previous purchases (58%) are also favored
31%	of consumers wish their shopping experience was more personalized than it currently is
20%	have never experienced any kind of personalized offers/promotions based on previous purchases, and 19% have never received product recommendations based on previous purchases

MC MARKETINGCHARTS.COM

Source: Infosys

The Long Tail



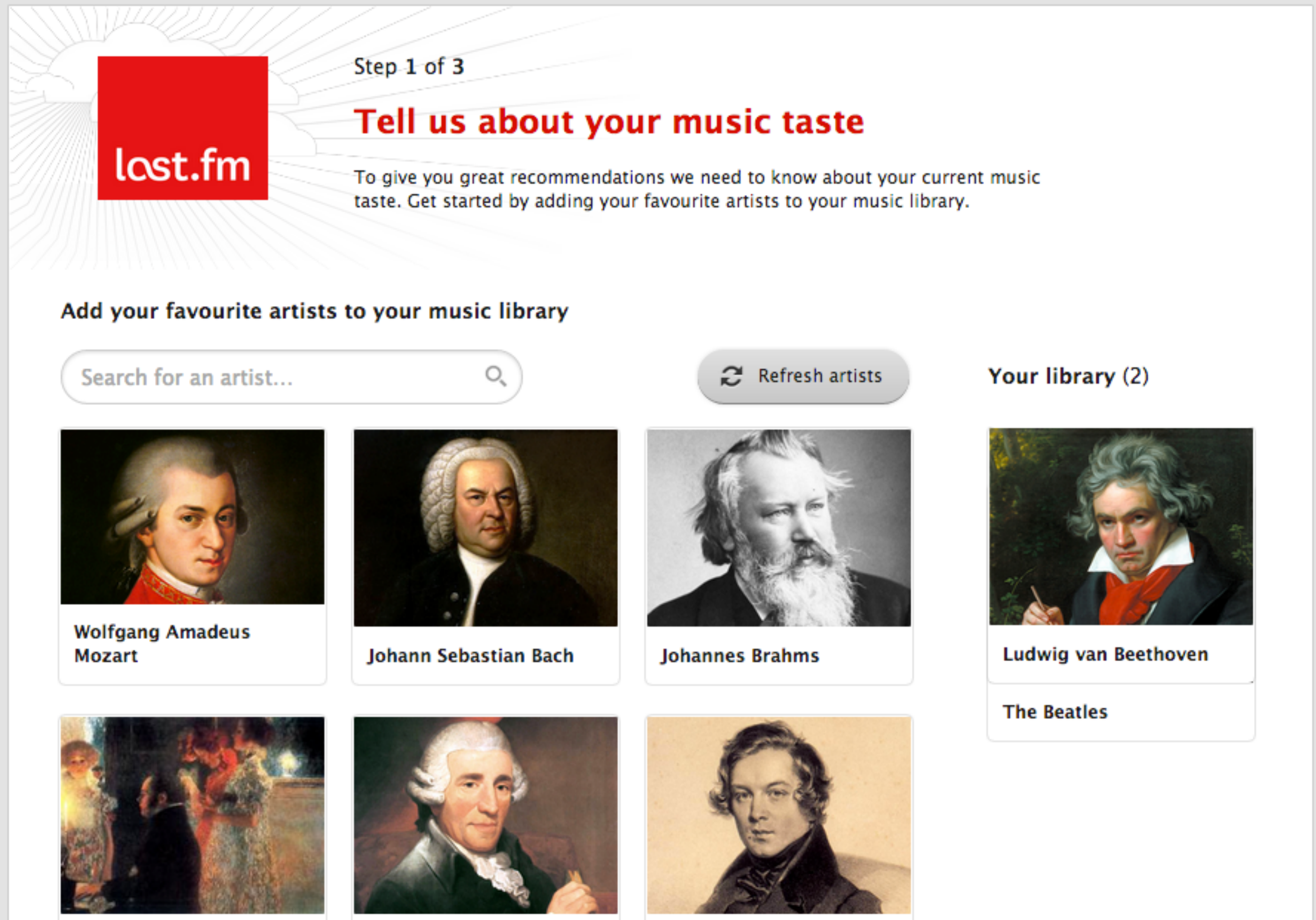
- Economic model in which the market for **non-hits** (typically large numbers of low-volume items) could be significant and sometimes even greater than the market for **big hits** (typically small numbers of high-volume items).

Goal

- **Recommend items that are good for you!**
  - relevant
  - improve well being
  - rational choices
  - *optimal*

Step 1: Preference Elicitation

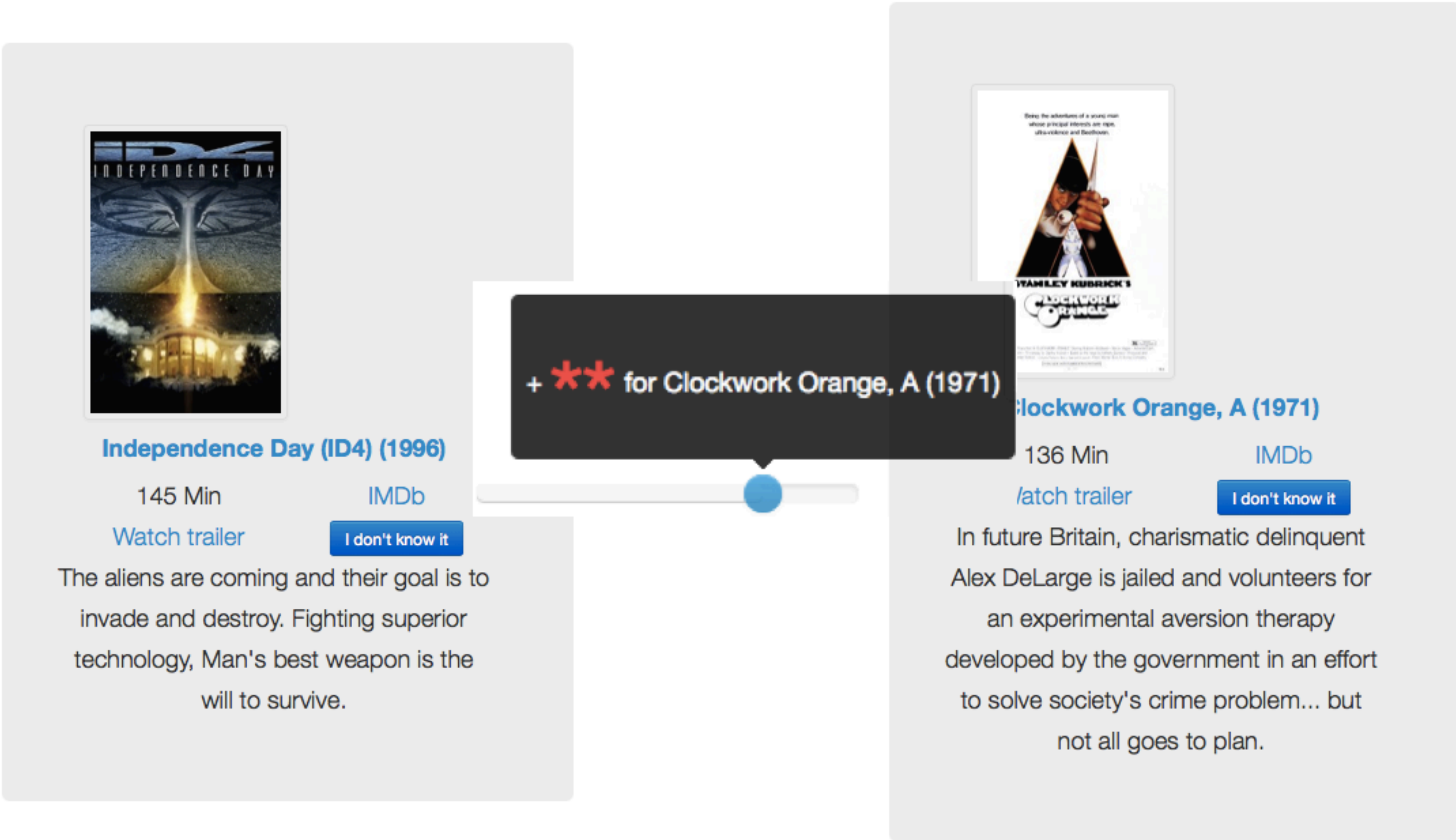
Last.fm – Preference Elicitation



Rating Recommendations

Alternative Methods

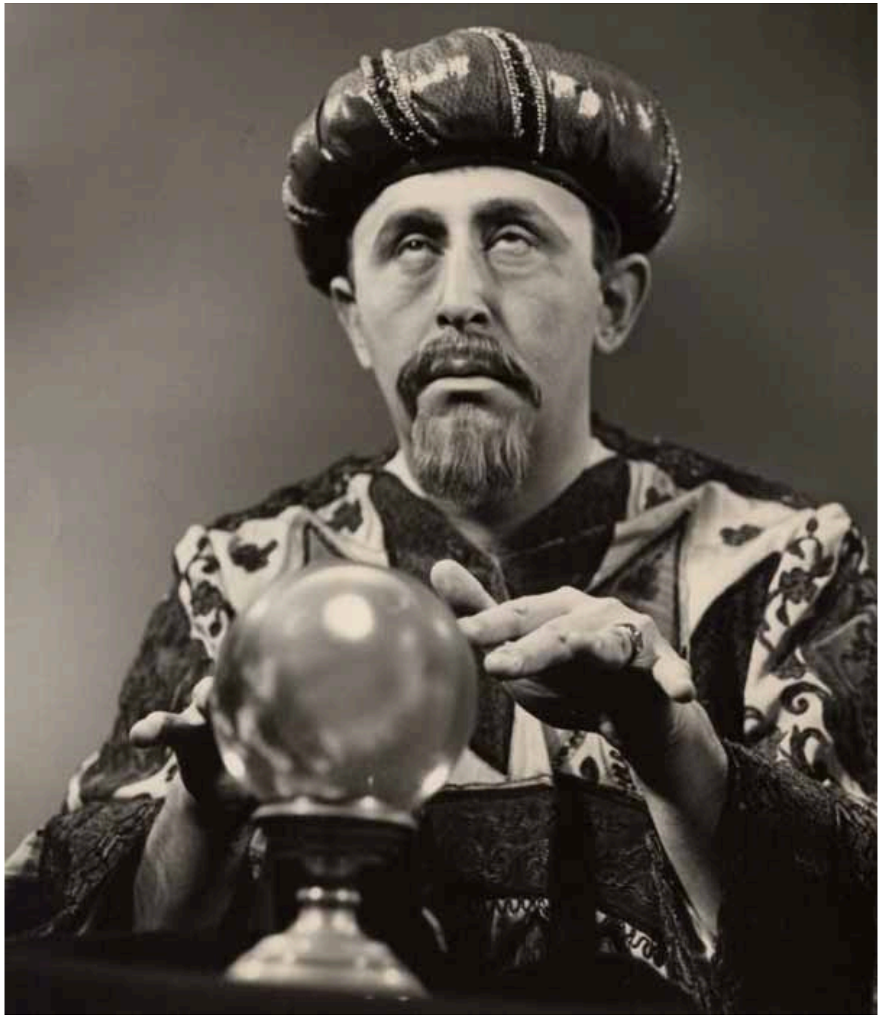
Like



Remembering

- D. Kahneman (nobel prize): what we remember about an experience is determined by (**peak-end rule**)
  - *How the experience felt when it was at its peak (best or worst)*
  - *How it felt when it ended*
- We rely on this summary later to remind how the experience felt and decide whether to have that experience again
- *So how well do we know what we want?*
  - It is doubtful that we prefer an experience to another very similar just because the first ended better.

Step 2: Model Building



Movie rating data

Training data

user	movie	date	score
1	21	5/7/02	1
1	213	8/2/04	5
2	345	3/6/01	4
2	123	5/1/05	4
2	768	7/15/02	3
3	76	1/22/01	5
4	45	8/3/00	4
5	568	9/10/05	1
5	342	3/5/03	2
5	234	12/28/00	2
6	76	8/11/02	5
6	56	6/15/03	4

Test data

user	movie	date	score
1	62	1/6/05	?
1	96	9/13/04	?
2	7	8/18/05	?
2	3	11/22/05	?
3	47	6/13/02	?
3	15	8/12/01	?
4	41	9/1/00	?
4	28	8/27/05	?
5	93	4/4/05	?
5	74	7/16/03	?
6	69	2/14/04	?
6	83	10/3/03	?

Matrix of ratings

Items

Users

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
a			1		4	5			4		3					2			4		2				
b			4							3							5	1		3					
c		5		4			4						3		5					4		5			
d								3				5				3			4		2			3	
e		3					5			4	5				5					1			5	4	
f			4				1		3	5		4	1		5	4	4		4				3		
g	2	4				4		2			5		1	4	5		4	2	4		5			4	
h			2		1		4		3	5		4	2		5	4	5						5		
i		1					3			5				5		4	4		5			4		3	
j			4			4				5			1		5		4		4				4		
k		5				4			2		5		1	5		4		2		4				2	
l					3			3				4	1		4		4	2	4					3	
m	5		3					5	3		5	4		5	5	3			4	4	5	4		4	
n			1		4	5				4	5		1	5		4		3		4		4	3		
o			4			4				5		4		5			4	2		5		5		3	
p				4			5								5	4		2	4	4	5	4		2	
q					3			3					1	5		4	4		4			4		3	
r		4			1	4		2					2		5		4				5	4		4	
s			2		4		4			5			1			4		2	4		4		5		
t		1		4			3					4		5	5		4			4				3	
u			2		1		4		3				1		5	4		2	4		5	4			
v					4	5				4	3		5			2					2			5	
w				2			2		3			5			4	5		4	2		3	4			
x	4			5				3		3				4	5					1					
y			1			3				2	3						3	3		5		4			

Item-to-Item Collaborative Filtering

target　　　neigh.　neigh.

	The Matrix	Titanic	Die Hard	Forrest Gump	Wall-E
John	5	1		2	2
Lucy	1	5	2	5	5
Eric	2	?	3	5	4
Diane	4	3	5	3	

- Suppose the prediction is made using two nearest-neighbors, and that the items most similar to "Titanic" are "Forrest Gump" and "Wall-E"
- Similarity of items: $w_{\text{titanic, forrest}} = 0.85$, $w_{\text{titanic, wall-e}} = 0.75$
- $r^*_{\text{eric, titanic}} = (0.85*5 + 0.75*4)/(0.85 + 0.75) = 4.53$

User-Based Collaborative Filtering

- A collection of n users U and a collection of m items I
- A n ´ m matrix of ratings r_{ui} , with $r_{ui} = ?$ if user u did not rate item i
- Prediction for user *u* and item *j* is computed as

$$r^*_{uj} = r_u + K \sum_{v \in N_j(u)} w_{uv} (r_{vj} - r_v)$$

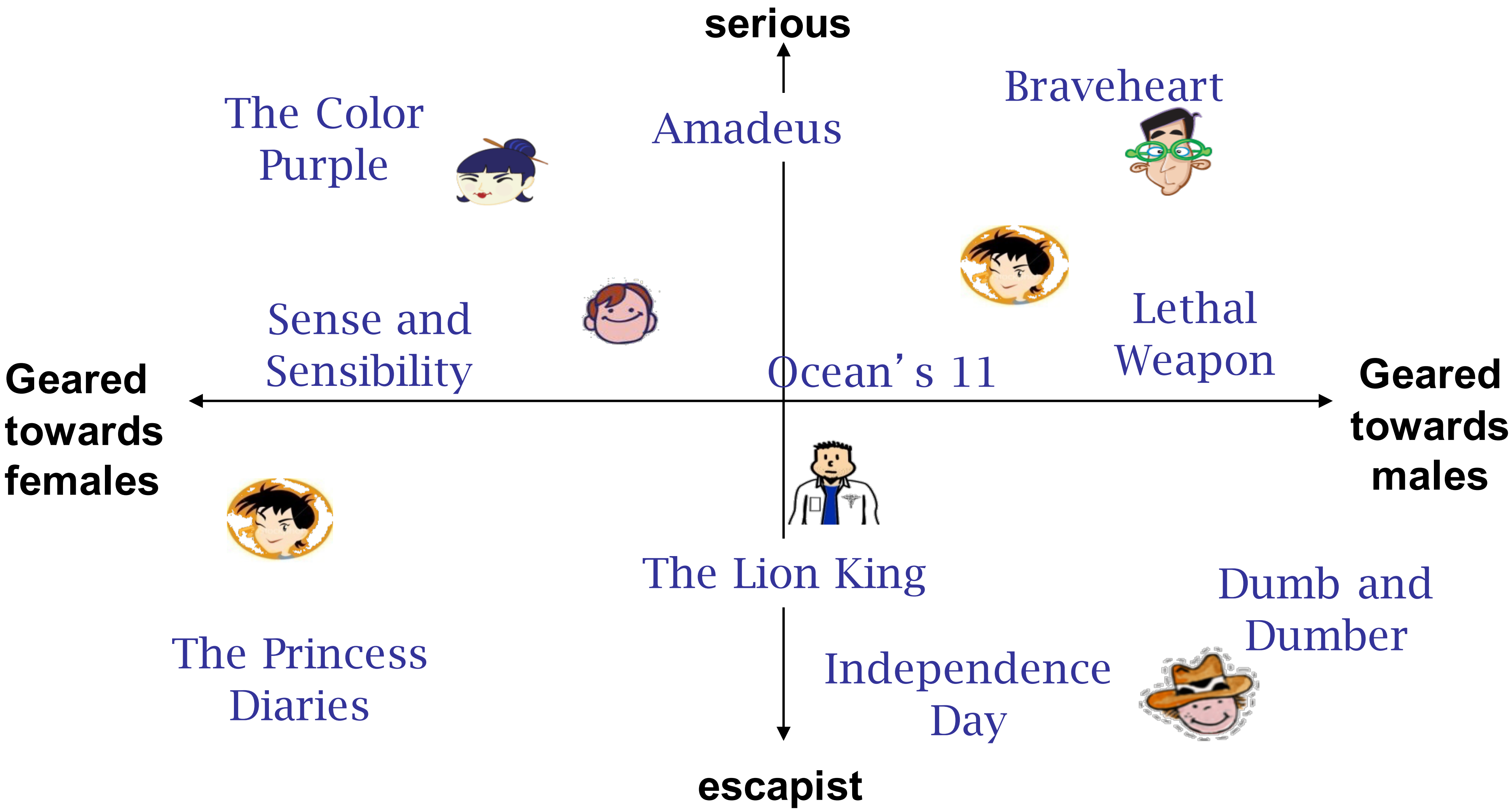
A set of neighbours of u that have rated j

- Where, r_u is the average rating of user u, K is a normalization factor such that the absolute values of w_{uv} sum to 1, and

$$w_{uv} = \frac{\sum_{j \in I_{uv}} (r_{uj} - r_u)(r_{vj} - r_v)}{\sqrt{\sum_{j \in I_{uv}} (r_{uj} - r_u)^2 \sum_{j \in I_{uv}} (r_{vj} - r_v)^2}}$$

Pearson Correlation of users u and v

Latent Factor Models

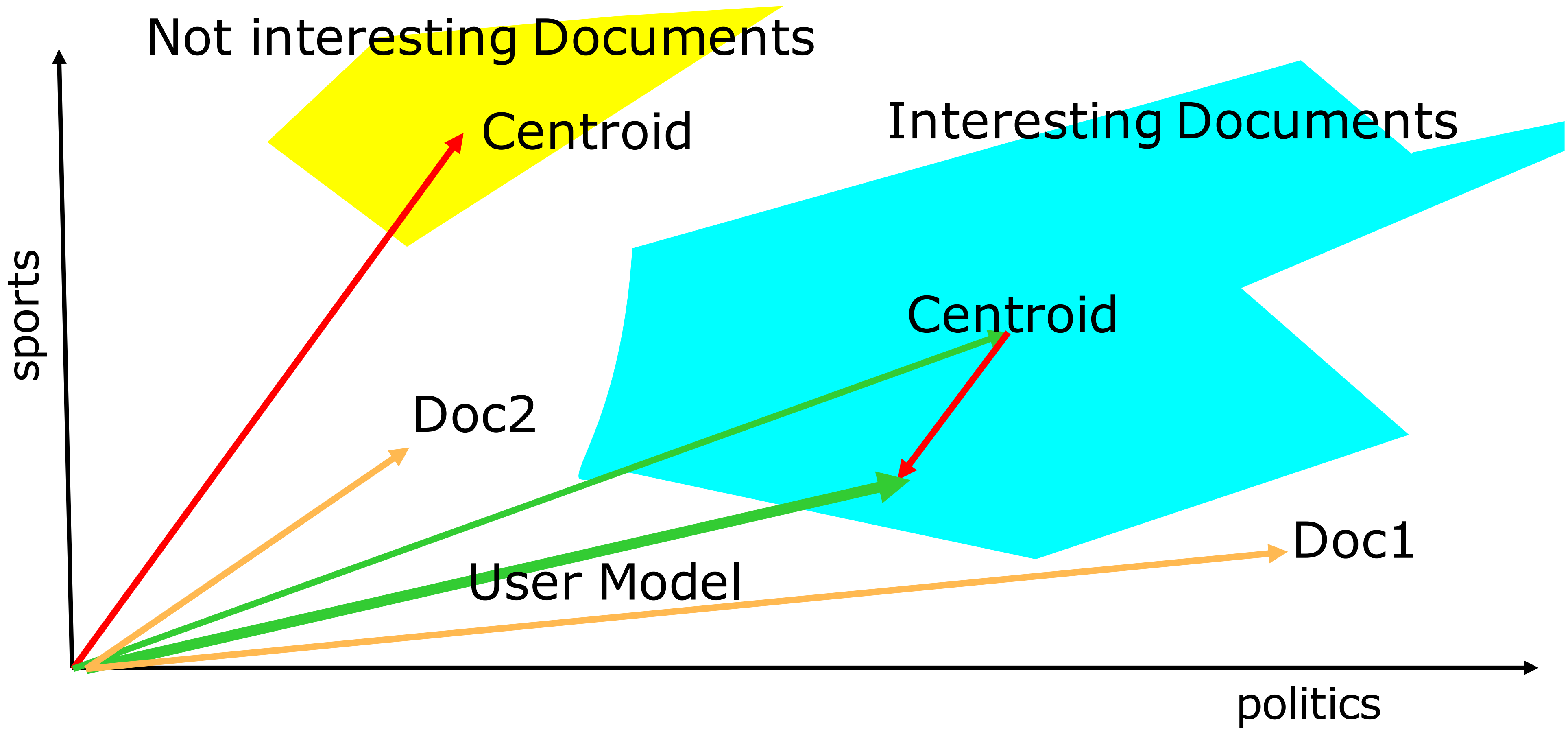


"Core" Recommendation Techniques

Technique	Background	Input	Process
Collaborative	Ratings from **U** of items in **I**.	Ratings from **u** of items in **I**.	Identify users in **U** similar to **u**, and extrapolate from their ratings of **i**.
Content-based	Features of items in **I**	**u**'s ratings of items in **I**	Generate a classifier that fits **u**'s rating behavior and use it on **i**.
Demographic	Demographic information about **U** and their ratings of items in **I**.	Demographic information about **u**.	Identify users that are demographically similar to **u**, and extrapolate from their ratings of **i**.
Utility-based	Features of items in **I**.	A utility function over items in **I** that describes **u**'s preferences.	Apply the function to the items and determine **i**'s rank.
Knowledge-based	Features of items in **I**. Knowledge of how these items meet a user's needs.	A description of **u**'s needs or interests.	Infer a match between **i** and **u**'s need.

[Burke, 2002]

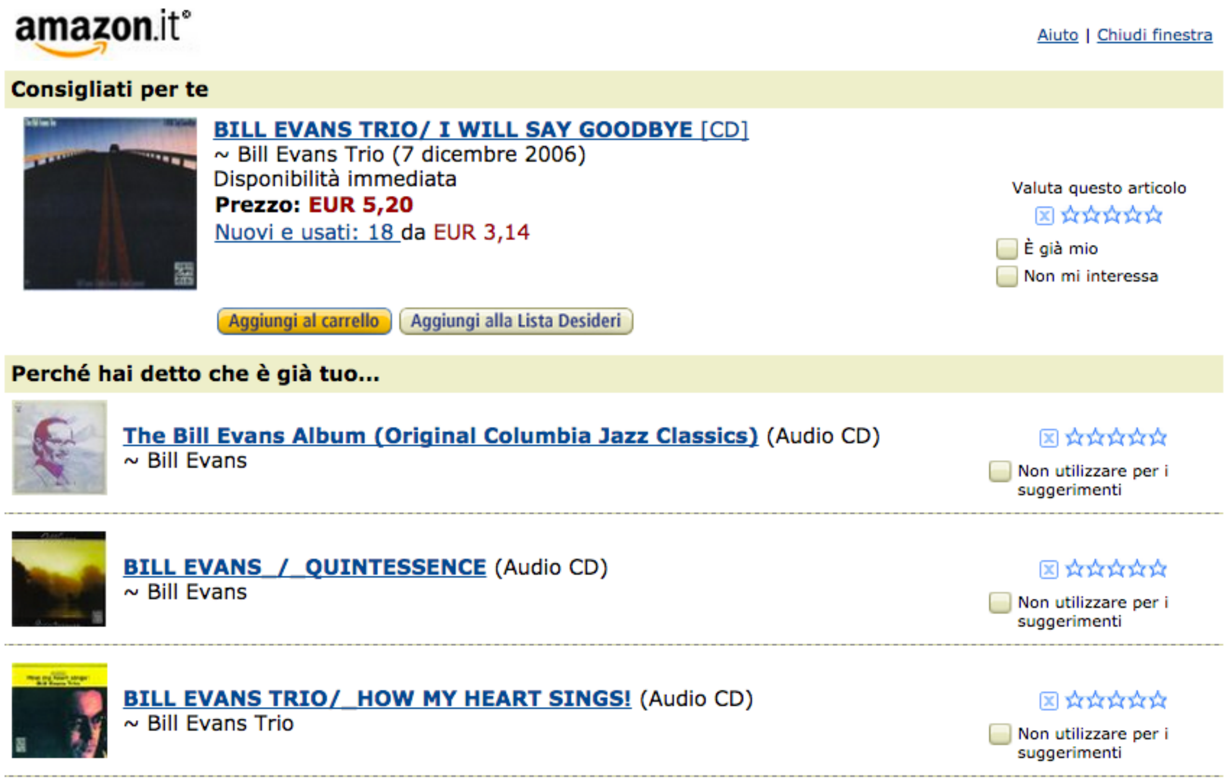
Content-Based Recommender with Centroid



Doc1 is estimated more interesting than Doc2

Recommendations are often wrong

- Recommenders tend to recommend items similar to those browsed or purchased in the past



Context-Aware Computing

- Gartner Top 10 strategic technology trends for IT

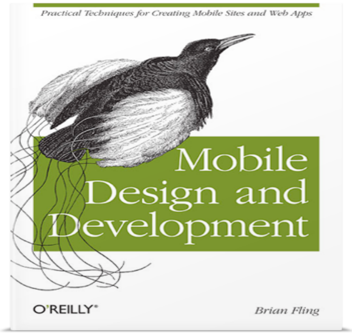
- *"Context-aware computing is a style of computing in which situational and environmental information about people, places and things is used to anticipate immediate needs and proactively offer enriched, situation-aware and usable content, functions and experiences."*

http://www.gartner.com/it-glossary/context-aware-computing-2

Google Now

https://www.google.com/landing/now/

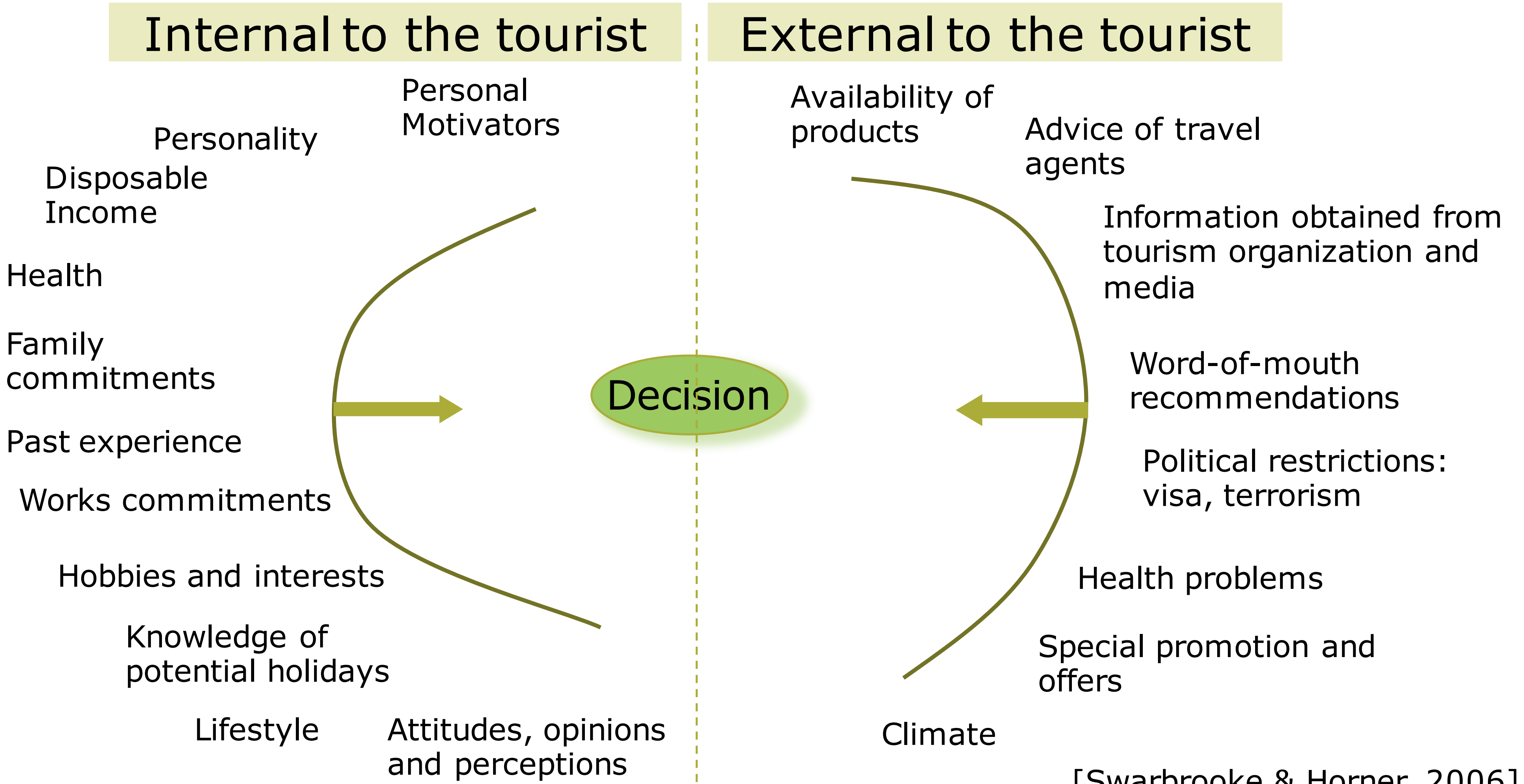
Types of Context - Mobile



[Fling, 2009]

- **Physical context**
  - time, position, and activity of the user, weather, light, and temperature ...
- **Social context**
  - the presence and role of other people around the user
- **Interaction media context**
  - the device used to access the system and the type of media that are browsed and personalized (text, music, images, movies, …)
- **Modal context**
  - The state of mind of the user, the user’s goals, mood, experience, and cognitive capabilities.

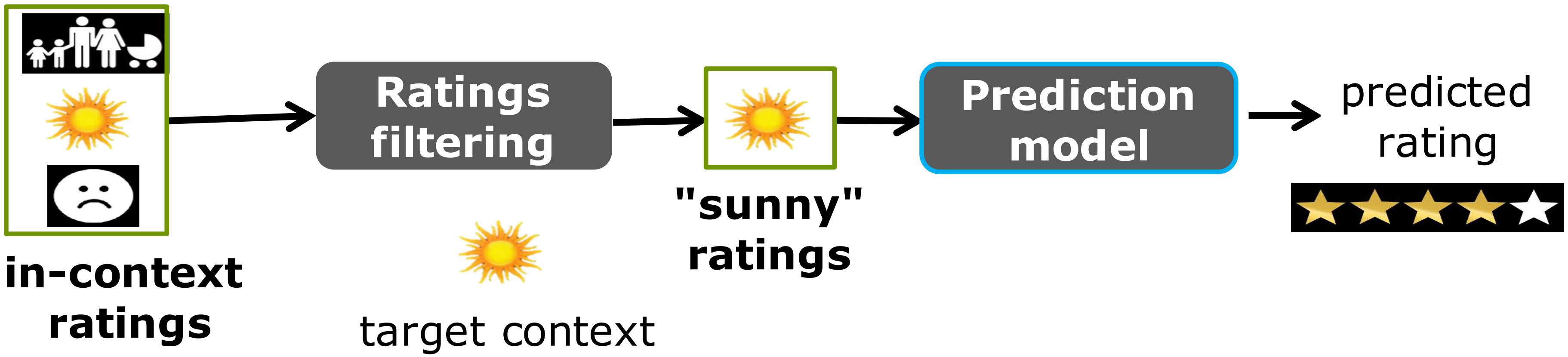
Factors influencing Holiday Decision



[Swarbrooke & Horner, 2006]

Traditional contextual pre-filtering

- Only ratings acquired in exactly the same context are used



- **Hypothesis:** pre-filtering can be enhanced by exploiting semantic similarities between contexts

Distributional semantics of context

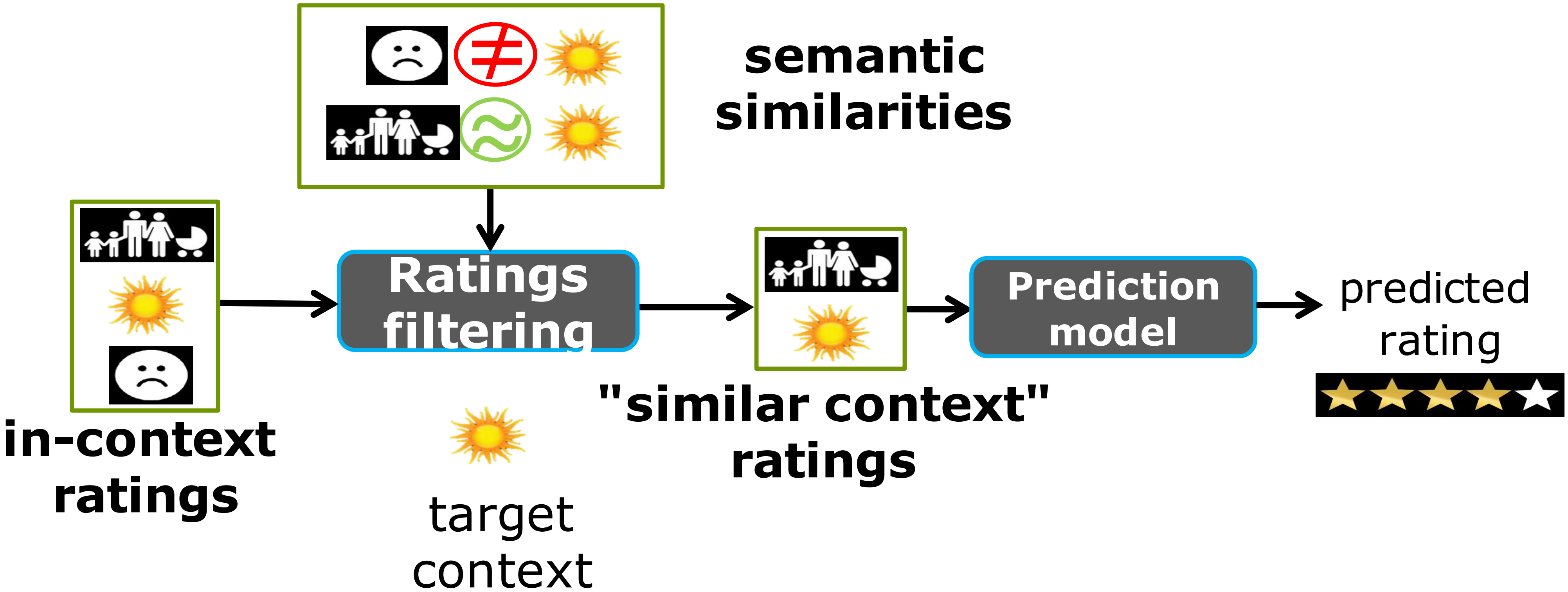
- **Assumption**: two contexts are similar if their composing conditions influence ratings similarly

$$\sum_{r_{uic} \in R_{ic}} (r_{uic} - \hat{r}_{ui}) \frac{1}{|R_{ic}|}$$

Condition	User1	User2	User3	User4	User5	User6	User7
	1	-0.7	0	0.9	0.1	-0.6	0
	0.7	-0.8	0.5	0.8	0.4	-0.2	0
	-0.5	0.7	0.2	-1	0.9	0.8	0.5

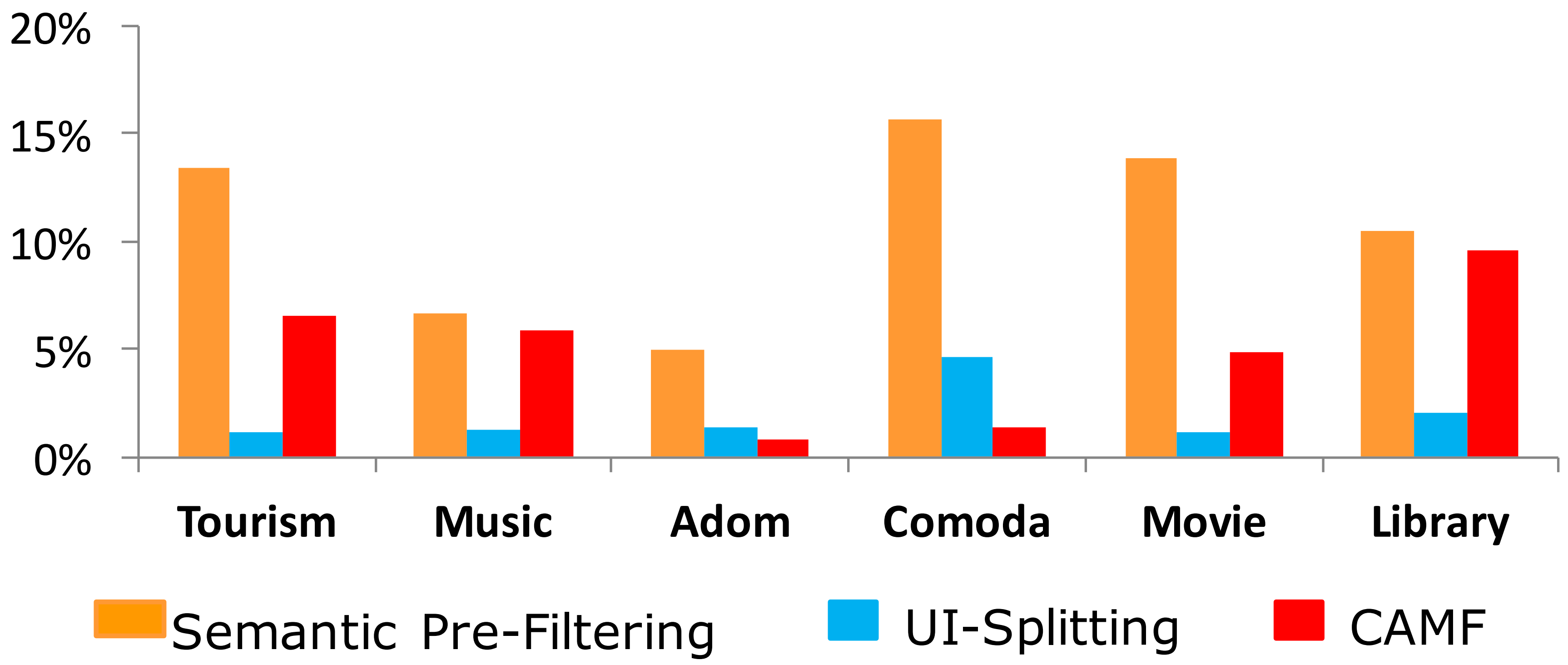
Semantic contextual pre-filtering

- **Key idea:** reuse ratings acquired in similar contexts



Semantic Pre-Filtering vs. state of the art

% = MAE (mean absolute error) reduction with respect to a context-free Matrix Factorization model (the higher, the better)

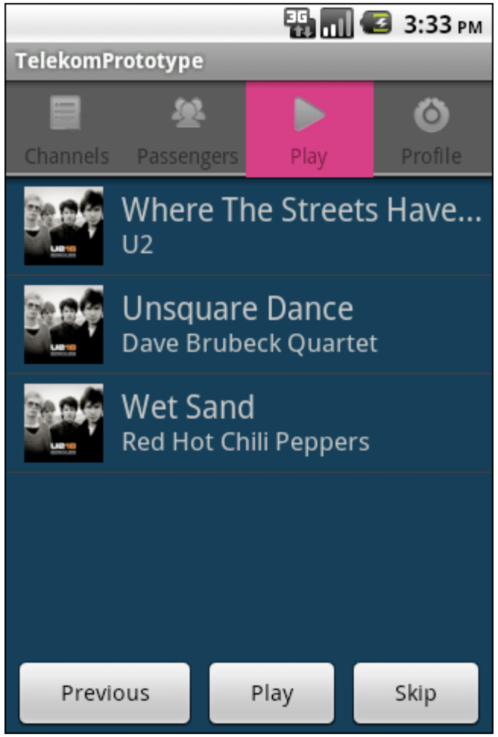


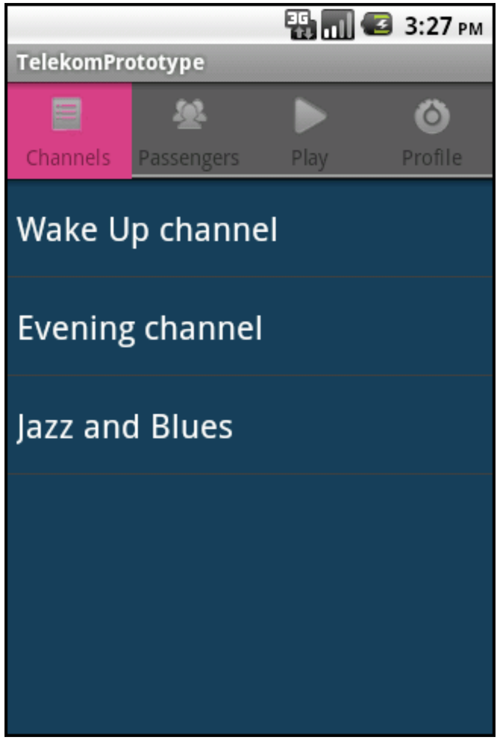
Group Recommendations

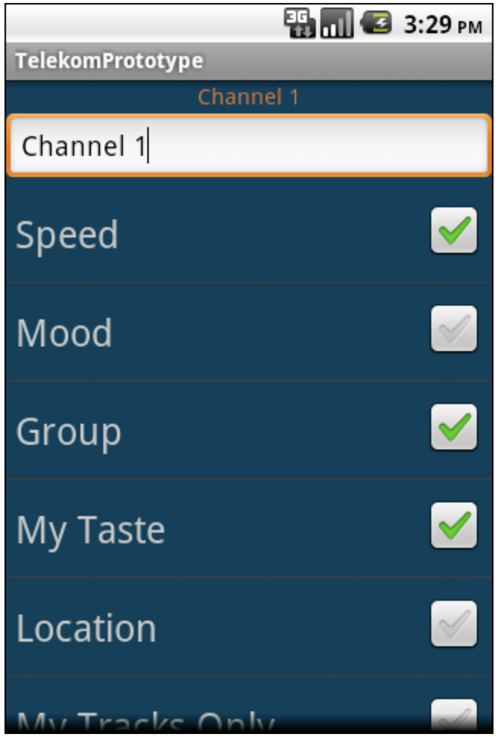
- Recommenders are usually designed to provide recommendations **adapted** to the **preferences** of a **single user**
- In many situations the recommended items are consumed by a **group of users**
  - *A travel with friends*
  - *A movie to watch with the family during Christmas holidays*
  - *Music to be played in a car for the passengers*

Mobile Application

- Recommending music compilations in a car scenario







[Baltrunas et al., 2011]

Effects of Groups on User Satisfaction

- **Emotional Contagion**
  - Other users being satisfied may increase a user's satisfaction (and viceversa)
  - Influenced by your personality and the social relationships with the other group members
- **Conformity**
  - The opinion of other users may influence your own expressed opinion
  - *Normative influence:* you want to be part of the group
  - *Informational influence:* opinion changes because you believe the group must be right.

First Mainstream Approach

- Creating the **joint profile** of a group of users

- We build a recommendation for this "average" user
- **Issues**
  - *The recommendations may be difficult to explain – individual preferences are lost*
  - *Recommendations are customized for a "user" that is not in the group*
  - *There is no well founded way to "combine" user profiles – why averaging?*

Second Mainstream Approach

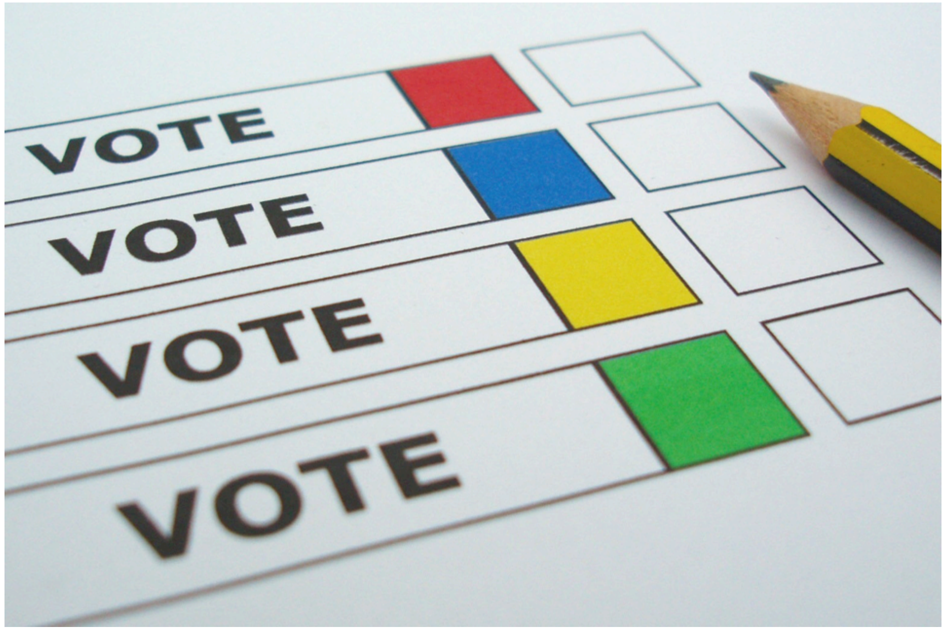
- Producing individual recommendations

- Then "aggregate" the recommendations:

- **Issues**
  - *How to optimally aggregate ranked lists of recommendations?*
  - *Is there any "best method"?*

Optimal Aggregation

- Paradoxically there is not an optimal way to aggregate recommendations lists
- Arrows' theorem: *there is no fair voting system*



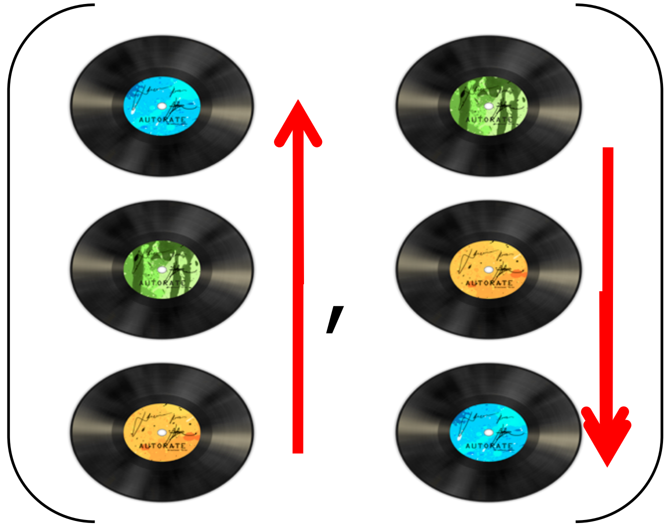
Arrow's Theorem

- No rank-order voting system can be designed that satisfies these three *fairness* criteria:
  - If every voter prefers alternative X over alternative Y, then the group prefers X over Y
  - If every voter's preference between X and Y remains unchanged when Z is added to the slate, then the group's preference between X and Y will also remain unchanged
  - There is no *dictator*: no single voter possesses the power to always determine the group's preference.

Kendall tau Distance

- The number of pairwise disagreements

dist



= 2

One item is preferred to the other

Average Aggregation

- Let $r^*(u,i)$ be either the predicted rating of u for i, or $r(u,i)$ if this rating is present in the data set
- Then the score of an item for a group g is
  - $r^*(g,i) = AVG_{u \in g} \{r^*(u,i)\}$
- Items are then sorted by decreasing value of their group scores $r^*(g, i)$
- ***Issue:*** *the recommended items may be very good for some members and less convenient for others*
- Hence … least misery approach

Least Misery Aggregation

- Let $r^*(u, i)$ be either the predicted rating of u for i, or $r(u, i)$ if this rating is present in the data set
- Then the score of an item for a group g is:
  - $r^*(g, i) = MIN_{u \in g} \{r^*(u, i)\}$
- Items are then sorted by decreasing value of their group scores $r^*(g, i)$
- *The recommended items have rather large predicted ratings for **all** the group members*
- *May select items that nobody hates but that nobody really likes (shopping mall case).*

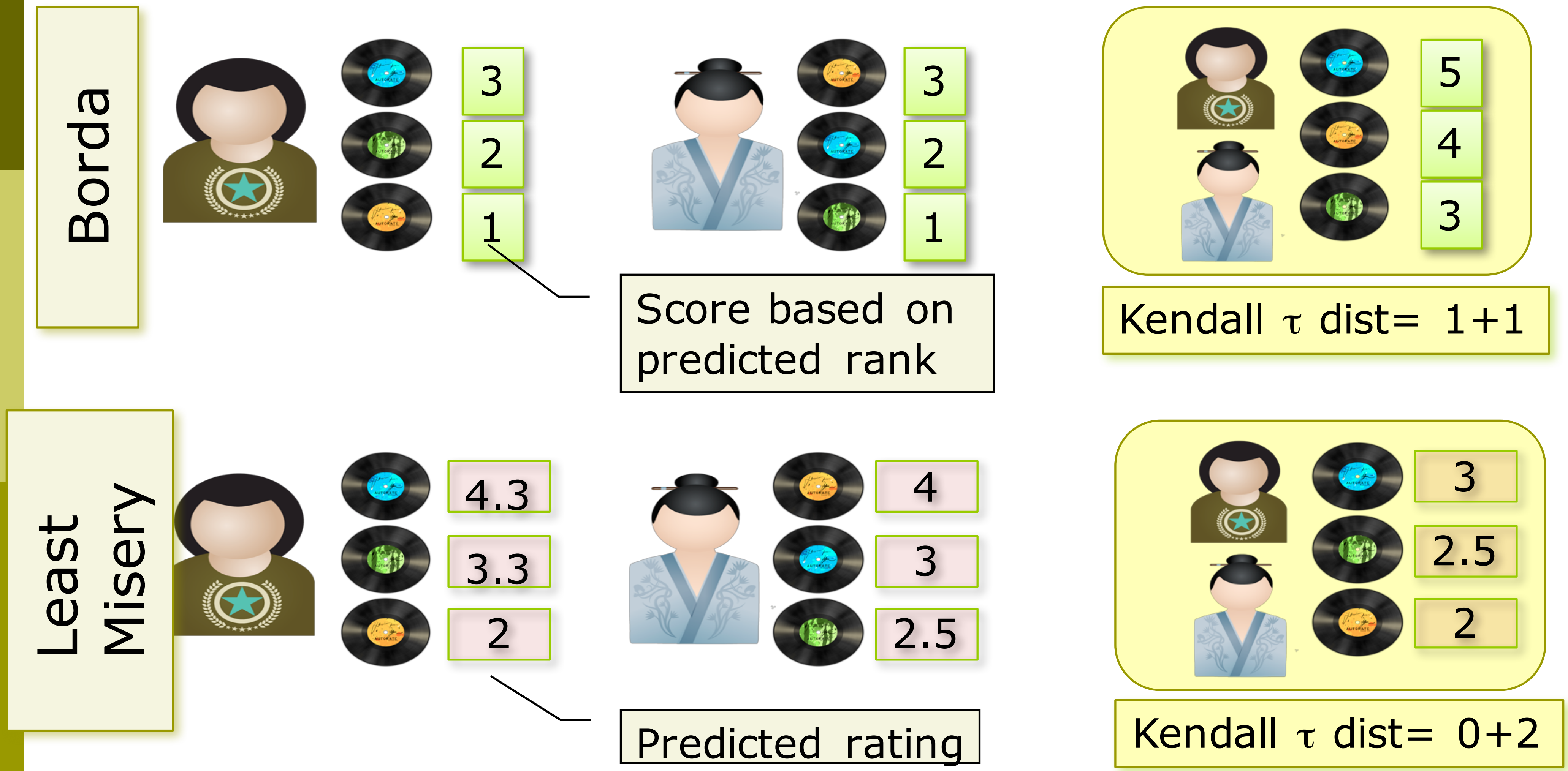
Borda Count Aggregation

- Each item in the ranking is assigned a **score** depending on its position in the ranking: the higher the rank, the larger the score is
- The last item i_n in the ranking of user u has $score(u,i_n) = 1$ and the first item has $score(u,i_1) = n$
- **Group score** for an item is calculated by adding up the item scores for each group member:

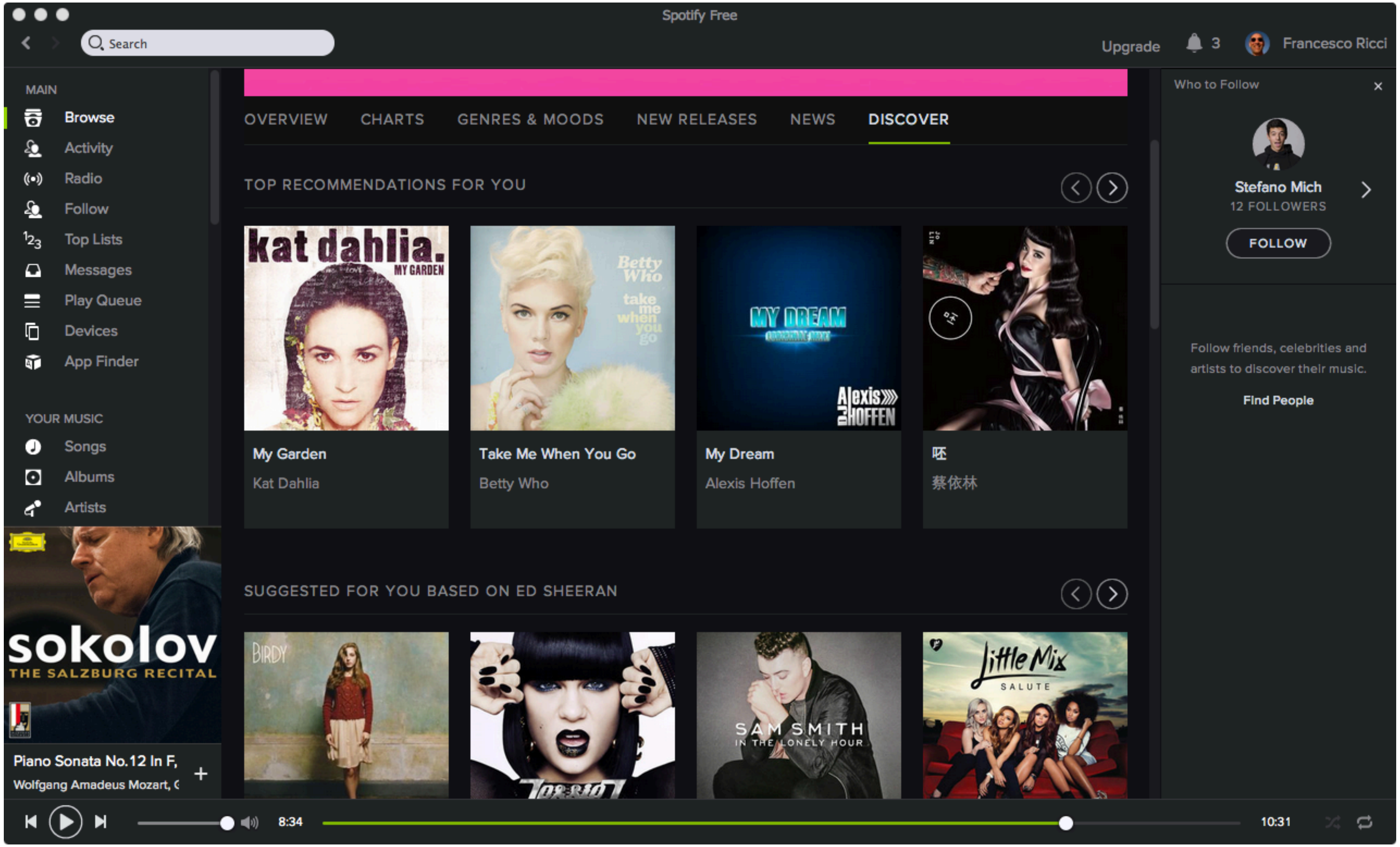
$$score(g,i) = \sum_{u \in g} score(u,i)$$

- Items are then ranked according to their group score.

Borda Count vs. Least Misery



Step 3: Recommendation Presentation



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Francesco Ricci
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Browse
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Follow
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Messages
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Devices
App Finder
YOUR MUSIC
Songs
Albums
Artists
sokolov
THE SALZBURG RECITAL
Piano Sonata No.12 In F,
Wolfgang Amadeus Mozart,
OVERVIEW
CHARTS
GENRES & MOODS
NEW RELEASES
NEWS
DISCOVER
TOP RECOMMENDATIONS FOR YOU
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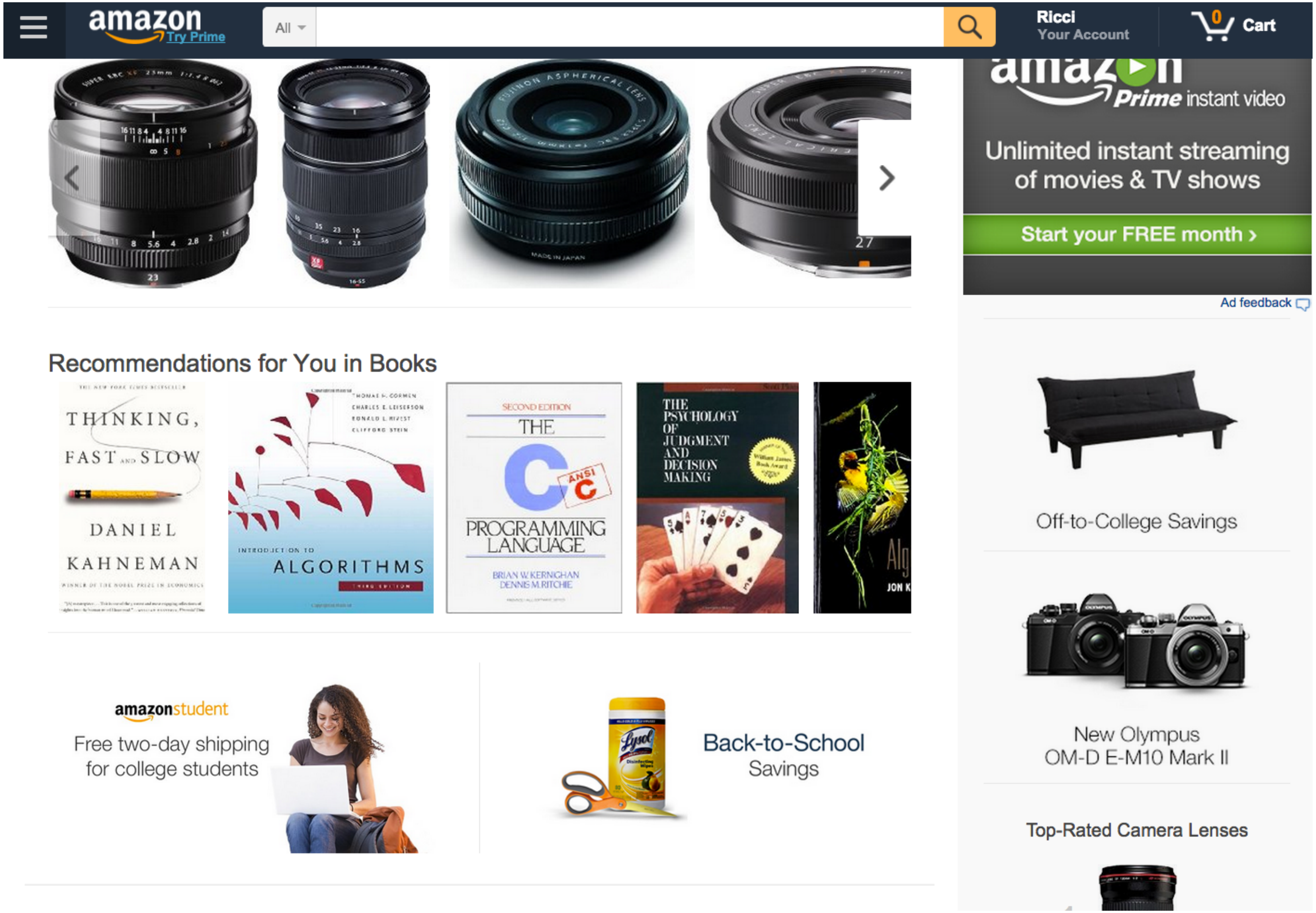
MY GARDEN
My Garden
Kat Dahlia
Betty Who
Take Me When You Go
Betty Who
MY DREAM
Alexis HOFFEN
My Dream
Alexis Hoffen
蔡依林
SUGGESTED FOR YOU BASED ON ED SHEERAN
BIRDY
SAM SMITH
IN THE LONELY HOUR
Little Mix
SALUTE
Who to Follow
Stefano Mich
12 FOLLOWERS
FOLLOW
Follow friends, celebrities and artists to discover their music.
Find People
8:34
10:31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Recommendations do *interact*

- The recommender ranks the items by their predicted ratings
- But when the items are presented to the user their perceived value is determined by the interaction context:
  - The quality of the presentation
  - The presence of other *competing* options

Anchoring

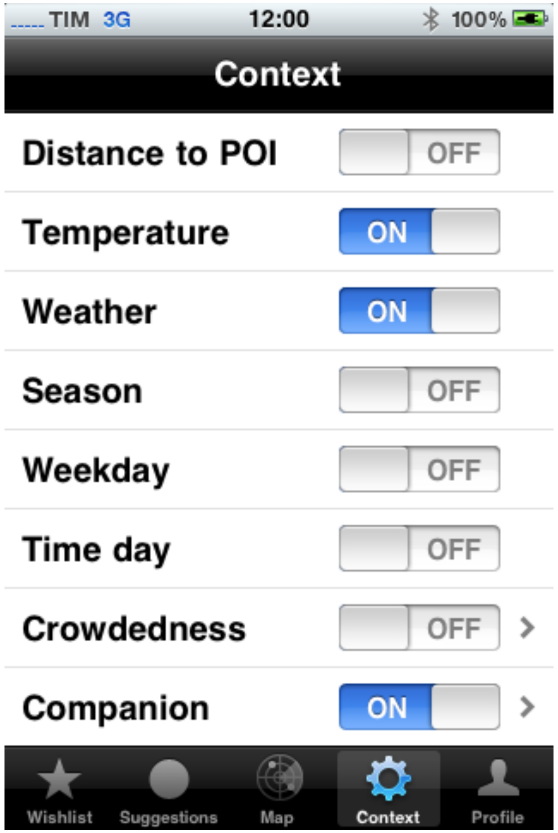
- How do we determine **what is reasonable to spend** for a race bicycle?
  - In an online shop that presents **only bicycles costing over 3.000E** we may believe that **1.500 is not enough**, or that a bicycle at that price will be a **bargain**
  - Even if nobody will select the highest-priced models, the shop can reap benefits from listing them – people is induced to buy the cheaper (but still expensive) ones.

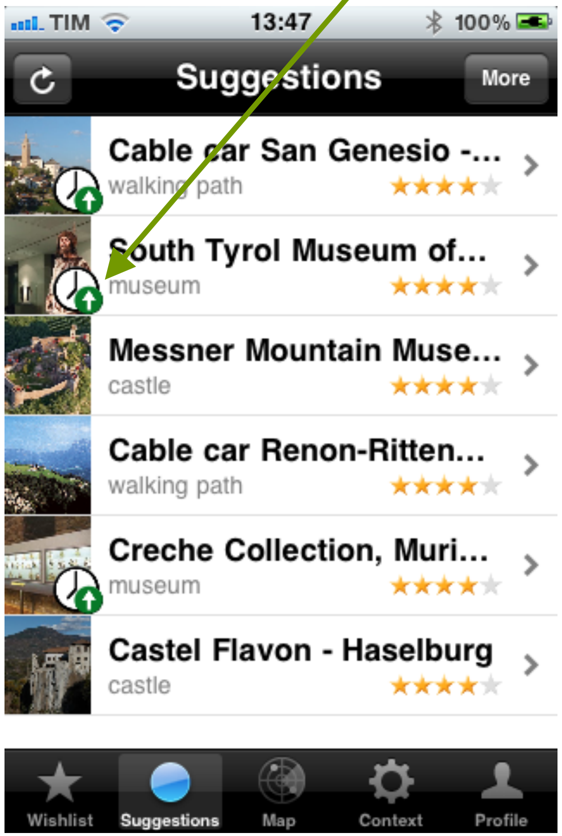
Colnago Ferrari

Dissatisfaction because of opportunity costs

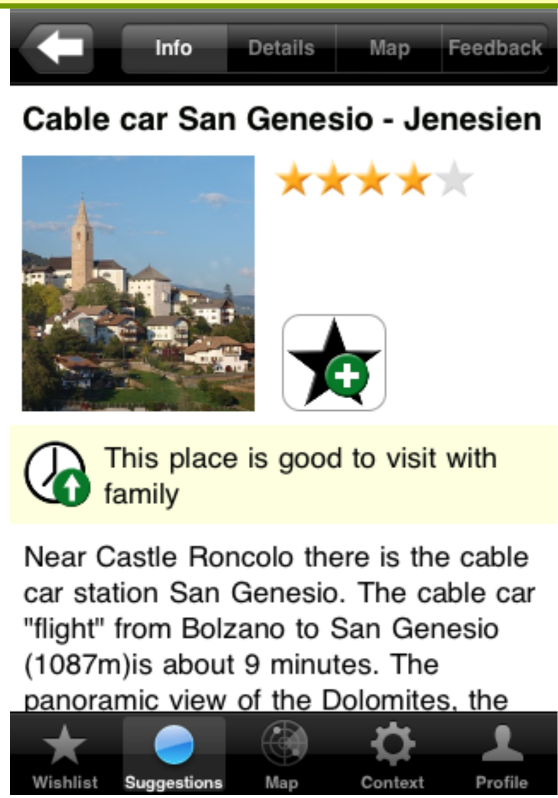
- A study in which people were asked how much they would be willing to pay for subscriptions to magazines [Brenner, Rottenstreich,& Sood, 1999]:
  - Some were asked about **individual magazines** or videos
  - Others were asked about these same items as **part of a group** with other magazines or videos
- Respondents placed a **higher value** on the magazine or the video **when they were evaluating it in isolation**
  - If evaluated as part of a group, **opportunity costs** associated with the other options **reduce the value of each of them.**

ReRex



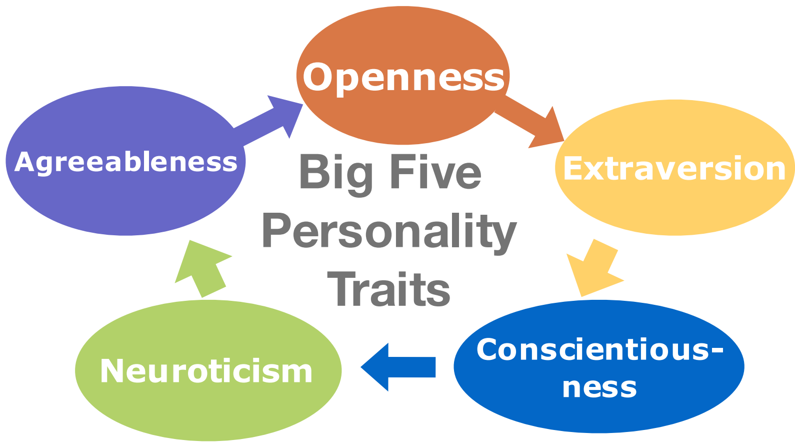


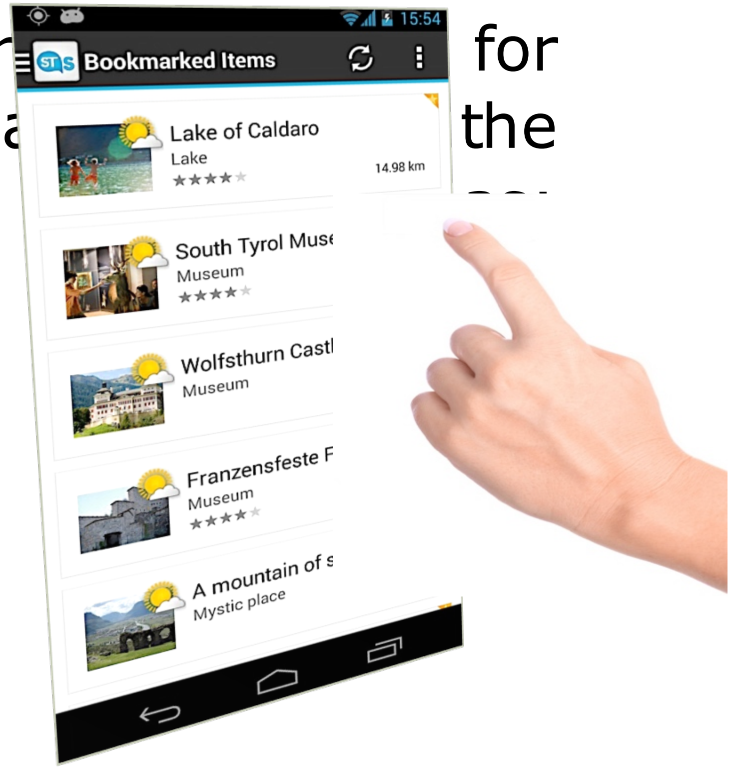
Context used to differentiate options and decrease opportunity cost



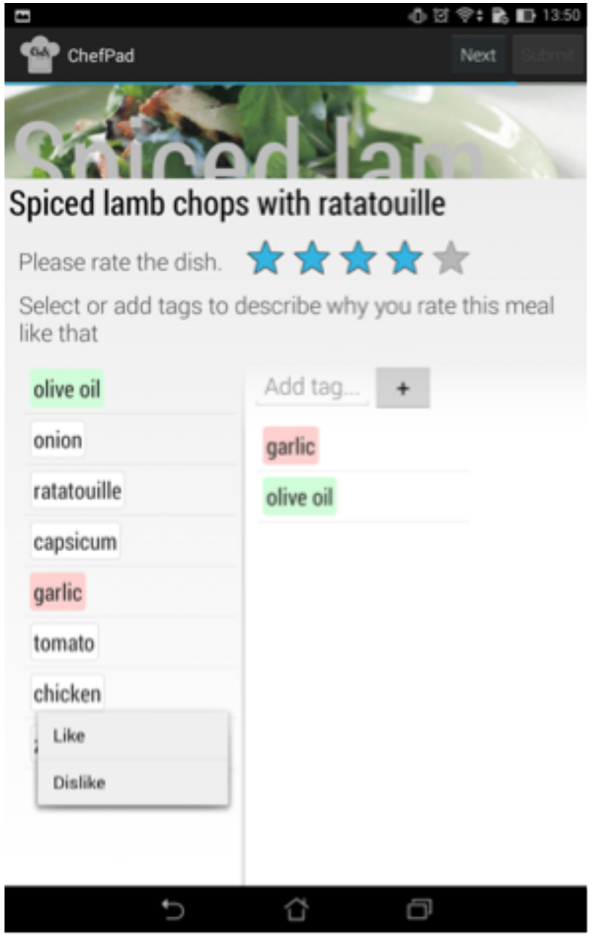
South Tyrol Suggest (STS)

- A mobile Android context-aware RS that recommends places of interests (POIs) from a total of 27,000 POIs in South Tyrol region
- STS computes rating pr for all POIs using the persona the users, the ratings, and 14 contextual weather forecast, mood, travel goal.



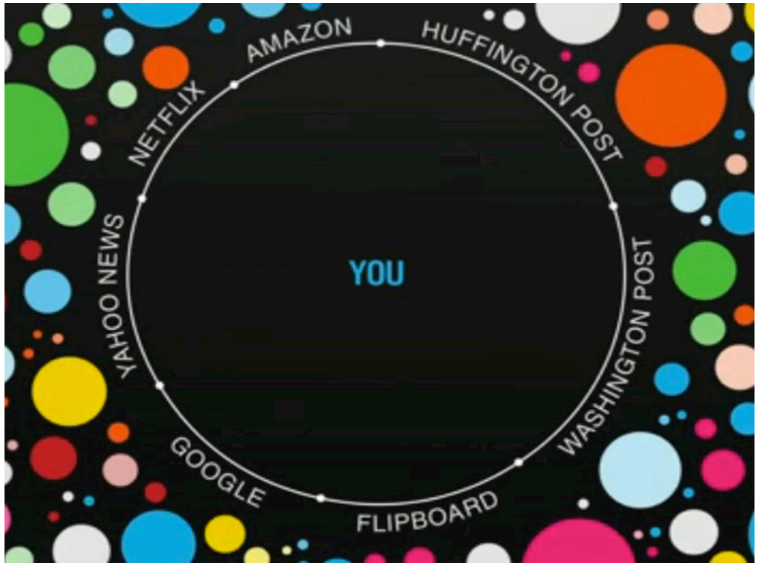


Food Advisor for a Family

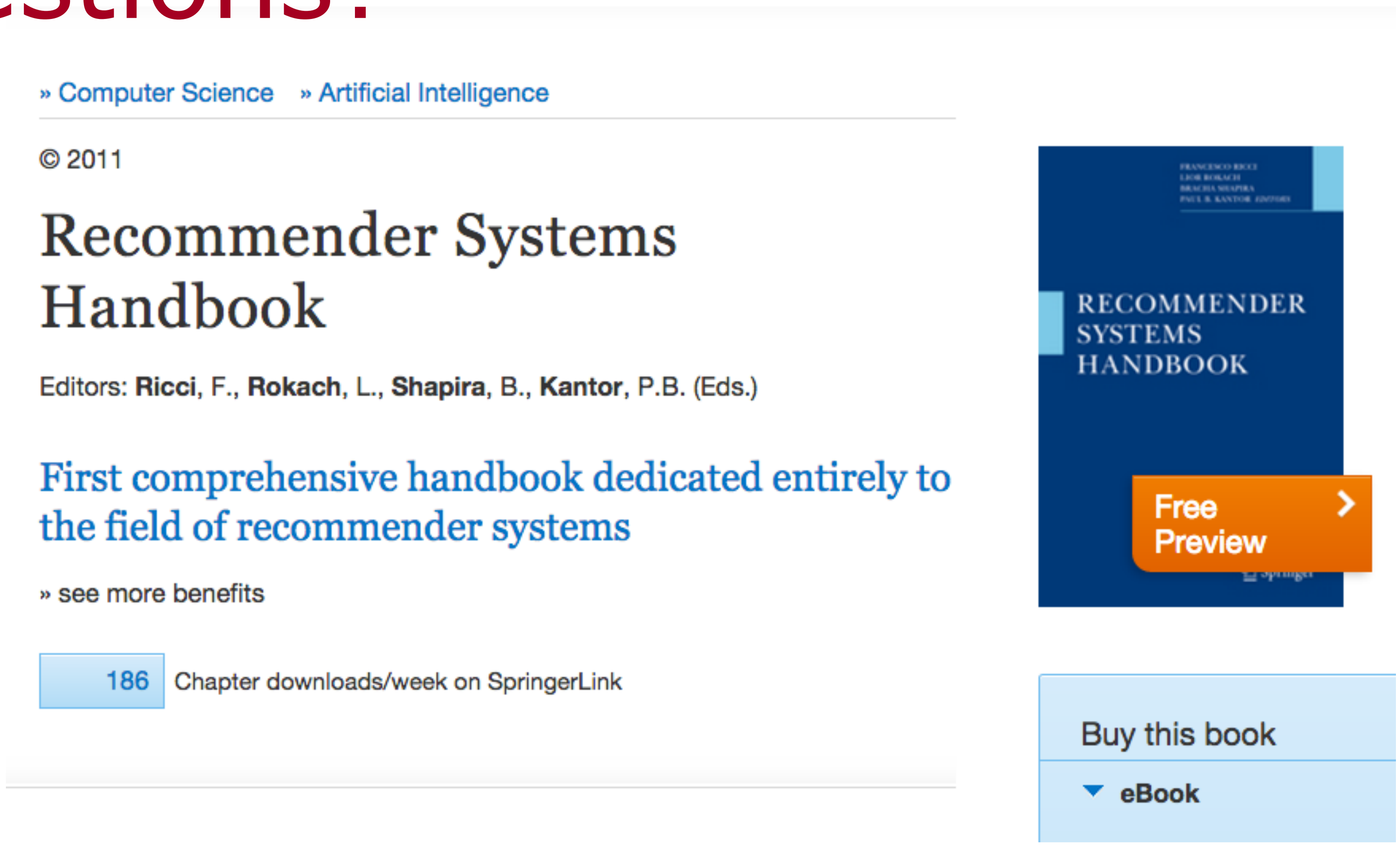


Problems and Issues

- Cold Start (new user and new item) - old items are less interesting
- Learning to interact
- Measuring sys. performance
- Filter Bubble
- How much to personalize
- When to contextualize
- How to deliver contextualized content?
- Multiple devices (synchronization)



Questions?



New edition is coming in 2015