

# Interacting with Recommender Systems

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# About the Presenters

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# About you

# Agenda

- ▶ 09:00 – 09:45
  - ▶ Introduction & Background
- ▶ 09:45 – 10:14
  - ▶ Interacting recommender systems - A review (Part I)
- ▶ 10:15 – 10:45
  - ▶ Coffee break
- ▶ 10:45 – 11:15
  - ▶ Interacting recommender systems - A review (Part II)
- ▶ 11:15 – 12:15
  - ▶ Explanations in recommender systems
  - ▶ Discussion

# Recommender Systems

## ► Application areas

You may also like



Jack & Jones  
JAMIE - Polo shirt - orange  
£21.00  
Free delivery & returns

### ALTERNATIVE PRODUCTS

Beko Washing Machine

Code: WMB81431LW

**£269.99**

Zanussi Washing Machine

Code: ZWH6130P

**£269.99**

Blomberg Washing Machine

Code: WNF6221

**£299.99**

### Related hotels...



Hotel 41

5 1,170 Reviews

London, England

Show Prices

Read Commented Recommended



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A screenshot of the Picassa web interface. At the top, there's a navigation bar with "Picassa™ -Webalben", "Startseite", "Meine Fotos", "Erkunden", and "Hochladen". Below that, it says "Empfohlene Fotos" and "Alle anzeigen". There are four thumbnail images displayed: a night view of a city skyline, the Eiffel Tower silhouette, a sunset over water, and a field of sunflowers.

Sources: Google Play, LinkedIn.com, Picasa.com

# Recommender Systems (RS)

- ▶ A pervasive part of our daily user experience
  - ▶ Customers who bought ... also bought
  - ▶ You may also like
  - ▶ Similar
  - ▶ Recommended / Suggested for you
  - ▶ People you may know
  - ▶ Who to follow
  - ▶ Others also liked
  - ▶ Jobs you may be interested in
  - ▶ Groups that you may like
  - ▶ Trending in your area

# User Interaction with RS

## ► Which user interaction?

- The system monitors what I do.
- And then shows me stuff.
- Which I can click on.

### Customers Who Bought This Item Also Bought



[Star Wars Trilogy Episodes I-III \(Blu-ray + DVD\)](#)

Hayden Christiansen

★★★★★ 2,042

Blu-ray

\$34.96



[Star Wars: The Force Awakens \(Blu-ray/DVD/Digital HD\)](#)

Harrison Ford

★★★★★ 10,002

Blu-ray

\$24.41



[Star Wars: Episode I - The Phantom Menace \(Widescreen Edition\)](#)

Ewan McGregor

★★★★★ 3,533

DVD

\$53.24



[Harry Potter: Complete 8-Film Collection \[Blu-ray\]](#)

Daniel Radcliffe

★★★★★ 6,945

Blu-ray

\$65.00

Source: Amazon.com

# Exercise

- ▶ Think of possible ways of interacting with a recommender system

# Design Space Examples

- ▶ Telling the system explicitly what you like
  - ▶ Global settings
  - ▶ Ratings
    - ▶ But how many options? How many categories?

**Personalize Google News**

Suggested for you	-	+
World	-	+
U.S.	-	+
Business	-	+
Technology	-	+
The Academy Awards	-	+
Entertainment	-	+
Sports	-	+
Science	-	+
Health	-	+

Add any news topic

Examples: Astronomy, New England Patriots, White House

## Rate this item



Sources: Facebook.com,  
Google.com



# Design Space Examples

- ▶ Different ways of showing you recommendations
  - ▶ But how many items to show?
    - ▶ One item only?
    - ▶ Two, three, or more items?
  - ▶ More than one list?
    - ▶ How many lists?
    - ▶ In which order?
  - ▶ Where on the screen?
    - ▶ At bottom, on the side, on top?
- ▶ When to recommend?
  - ▶ Always? Upon request? As notification?

# Design Space Examples

- ▶ What to display (in addition to a nice picture)?
  - ▶ Just the product/item info?
  - ▶ Feedback options?
    - ▶ Like /Dislike?
    - ▶ Or more?

**Tell us why**

I've already watched the video

I don't like the video

I'm not interested in this channel: **Jimmy Kimmel Live**

I'm not interested in recommendations based on:  
 **Wild Animals with Dave Salmoni**  
by Jimmy Kimmel Live

[Cancel](#) [Submit](#)

Source: Youtube.com

# Design Space Examples

- ▶ What to display (in addition to a nice picture)?
  - ▶ Maybe some explanation, but which one?
  - ▶ A predicted rating?

The screenshot shows a movie recommendation interface. On the left is the movie poster for "The Next Three Days" featuring Russell Crowe. To the right is a detailed movie card for "The Next Three Days". The card includes the title, release year (2010), rating (PG-13), and runtime (133 minutes). Below this is a plot summary: "When his wife is sent to jail on murder charges she fervently denies, a college professor hatches a meticulous plan for the ultimate prison escape." A "More Info" link is provided. Further down, it lists the starring actors (Russell Crowe, Elizabeth Banks) and director (Paul Haggis). A recommendation section follows, stating: "Based on your interest in: Iron Man 2, John Q and X-Men Origins: Wolverine". Below this, a prediction is shown: "Our best guess for Xavier:" followed by a 5-star rating icon. Two buttons are at the bottom: "Not interested" and "In Instant Queue". A green arrow points from the "In Instant Queue" button towards the right edge of the slide.

Source: Netflix.com

# Design Space Examples

- ▶ What to display (in addition to a nice picture)?
  - ▶ Maybe some explanation, but which one?
  - ▶ Or our logic to recommend this?

## Recommended for you



### [Guardians of the Galaxy \[Blu-ray\]](#)

**Blu-ray** ~ Chris Pratt (8 Jan 2015)

In stock

**Price: EUR 9,99**

[73 used & new from EUR 8,75](#)

Rate this item



- I own it
- Not interested

[Add to Cart](#)

[Add to Wish List](#)

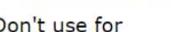
## Because you purchased...



### [Mad Max: Fury Road \[Blu-ray\]](#) (Blu-ray)

**DVD** ~ Charlize Theron

Rate this item



- Don't use for recommendations

Source: Amazon.com

# Design Space Examples

- ▶ It could even be a dialog

The screenshot shows a web browser window for the VIBE virtual adviser. The title bar reads "http://www.configworks-gmbh.online.de - VIBE - the virtual adviser for the Warmbad-Villach spa reso...". The main content area features a woman in a red top thinking with her hand on her chin. A text box says: "Think about what you'd really like and I'll see what I can come up with for you." Below her, a question asks: "Mr Jannach, how do you feel right now? What would you like to improve if it were possible?" A list of checkboxes follows:

- I feel quite tired and would like to recharge my batteries
- I would like to improve my fitness.
- I would like to lose some weight and be slimmer.
- I often feel tense and sometimes have problems with my back.
- I would like to do something about my appearance and my image.
- I feel perfectly healthy and would simply like to relax for a few days.

At the bottom are buttons for "Direct to result", "Back", "Next", and a "Fertig" button.

# Design Space Examples

- ▶ It could even be a dialog

The screenshot shows a web-based application window titled "VIBE - the virtual adviser for the Warmbad-Villach spa resort". On the left, there's a large image of a woman in a red dress gesturing with her hands. A speech bubble from her contains the text: "Wonderful, we've now got to your final selection. Here's my recommendation for you ...". The main content area displays two package recommendations:

**Feel well week**

Length of stay:	per week (7 nights) per person
Meals:	Half board
Accommodation:	The Warmbaderhof
Dates:	At any season
Rate in single room:	from € 1595
Rate in double room:	from € 1595

[Details](#) [Why?](#)

**I can also recommend the following packages:**

- You can book a personal massage or a whole massage programme for your stay at any time.

**Golf & Spa**

Length of stay:	per week (7 nights) per person
Meals:	Half board
Accommodation:	The Warmbaderhof
Dates:	01.04.2008-31.10.2008

[Details](#) [Why?](#)

At the bottom, there are navigation buttons: Back, Restart, Print, Online-request, and a Fertig button.

# Design Space Examples

- ▶ It could even be a dialog

The screenshot shows a web browser window for 'VIBE - the virtual adviser for the Warmbad-Villach spa resort'. The title bar includes the URL <http://www.configworks-gmbh.online.de>, the page title 'VIBE - the virtual adviser for the Warmbad-Villach spa reso...', and standard window controls (minimize, maximize, close).

The main interface features a logo for 'VIBE VIRTUAL ADVISER' with a stylized 'V' icon. At the top right are links for 'HOME', 'CALL BACK SERVICE', and 'RECOMMENDATION'.

A large image of a woman with dark hair, wearing a red top, is on the left. She is pointing upwards with her right index finger. A speech bubble next to her says: 'You're bound to ask yourself why I recommended the following. I'll be happy to explain...'. To the right of the image is a box containing the heading 'My arguments specially for you.' followed by a bulleted list of reasons:

- I am happy to have found autumn packages for you, as you wished. If you want more suggestions for a specific date, you'll have to use the detailed advice option (more questions).
- We have a whole range at the Warmbad-Villach spa resort to suit your request Leisure and activities programme & Long walks. Ask about them.
- Our comprehensive supporting programme of cultural events (Carinthian Summer Music Festival, Villach Carnival, exhibitions at the Warmbad culture club, Jazz Over Villach, etc.) all year round and attractions in the vicinity will round off your stay at the
- Do you want to feel fit and healthy? Our sports and activities programmes respond to your wishes

At the bottom of the window, there are 'Back' and 'Fertig' (Done) buttons, along with standard window control buttons.

# Recommendation Approaches

- ▶ Which kind of interactions you can support depends on the underlying algorithm(s)
  - ▶ If you show preference predictions, you must predict ratings and not just rank items
  - ▶ If you use a complex prediction algorithm, providing explanations can be challenging
  - ▶ If you support feedback on recommendations, you should be able to immediately consider it
  - ▶ If you want to interact with users with a chatbot, many more challenges will emerge
- ▶ Basic background knowledge and terminology of RS will be presented next

# Background on Recommenders

- ▶ Topics
  - ▶ Why using recommender systems at all?
  - ▶ What are the basic technical approaches?
    - ▶ Collaborative filtering
    - ▶ Content-based filtering
    - ▶ Knowledge-based approaches
    - ▶ Hybrids

# Why Using Recommenders?

- ▶ Value for the customer
  - ▶ RS helps user find things that are interesting
  - ▶ RS helps user narrow down the set of choices
  - ▶ RS helps user explore the space of options
  - ▶ RS helps user discover new things, entertainment
  - ▶ ...
- ▶ Value for the provider
  - ▶ Increased sales, click trough rates, conversion etc.
  - ▶ Increased trust and customer loyalty
  - ▶ More opportunities for promotion, persuasion
  - ▶ More knowledge about customers
  - ▶ ...

Jannach, D. and Adomavicius, G.: Recommendations with a Purpose, ACM Conference on Recommender Systems, RecSys 2016, Boston, MA, pp. 7-10

# A Possible Algorithmic Task

- ▶ Given
  - ▶ The profile of the "active" user and possibly some situational context
- ▶ Compute
  - ▶ A relevance (ranking) score for each recommendable item
- ▶ The profile ...
  - ▶ ... can include past user ratings (explicit or implicit), demographics and interest scores for item features
- ▶ The problem ...
  - ▶ ... is to learn a function that predicts the relevance score for a given (typically unseen) item

# Recommendation Paradigms

Recommender systems  
reduce information  
overload by estimating  
relevance



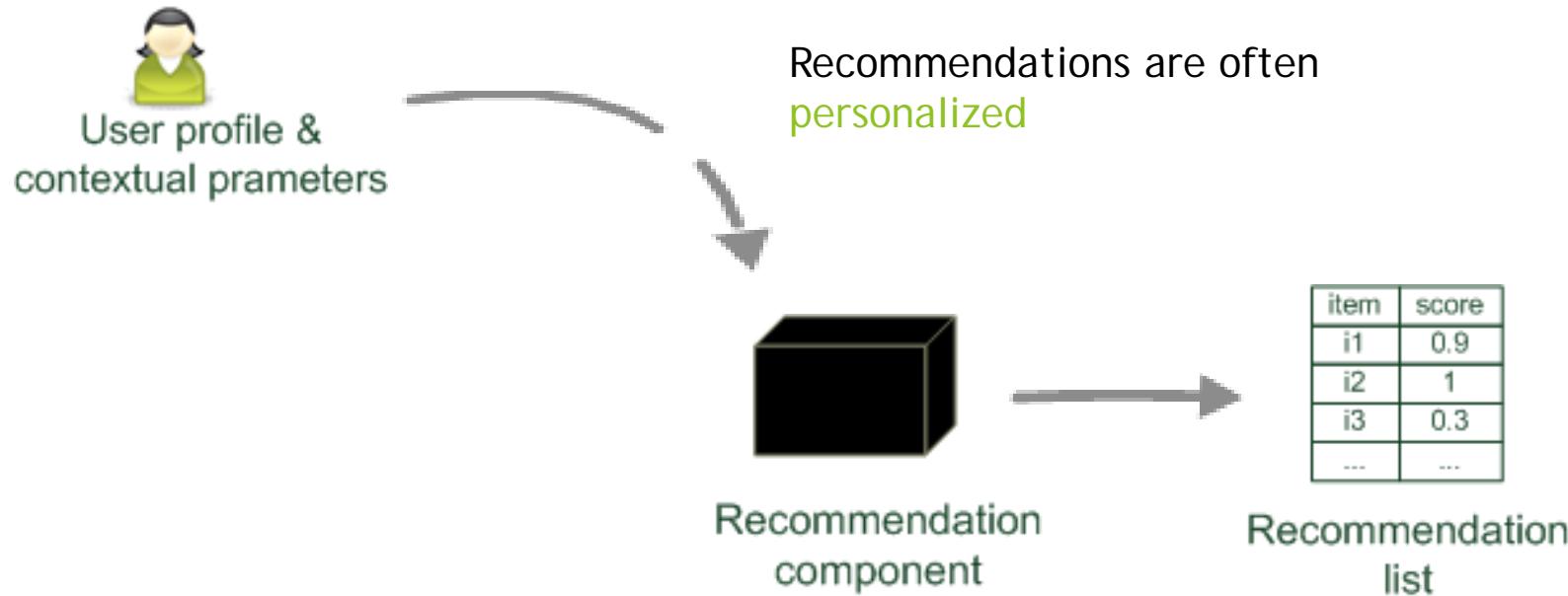
Recommendation  
component



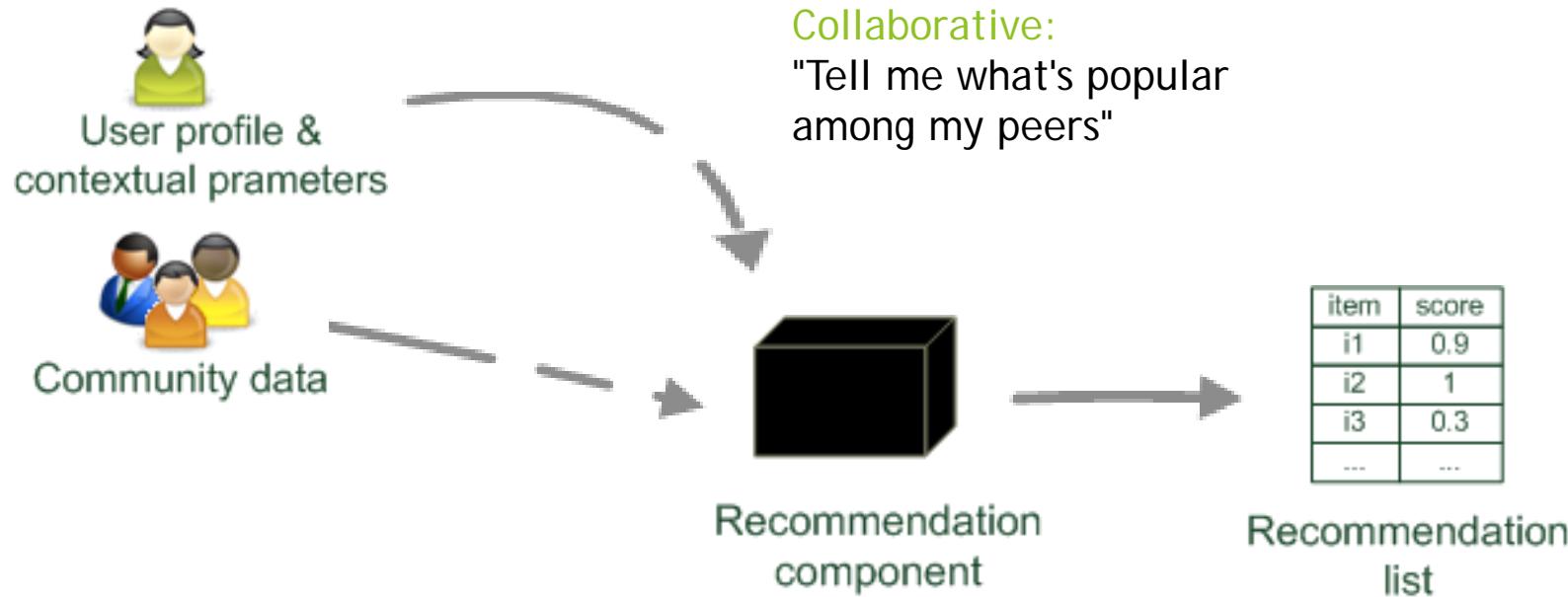
item	score
i1	0.9
i2	1
i3	0.3
...	...

Recommendation  
list

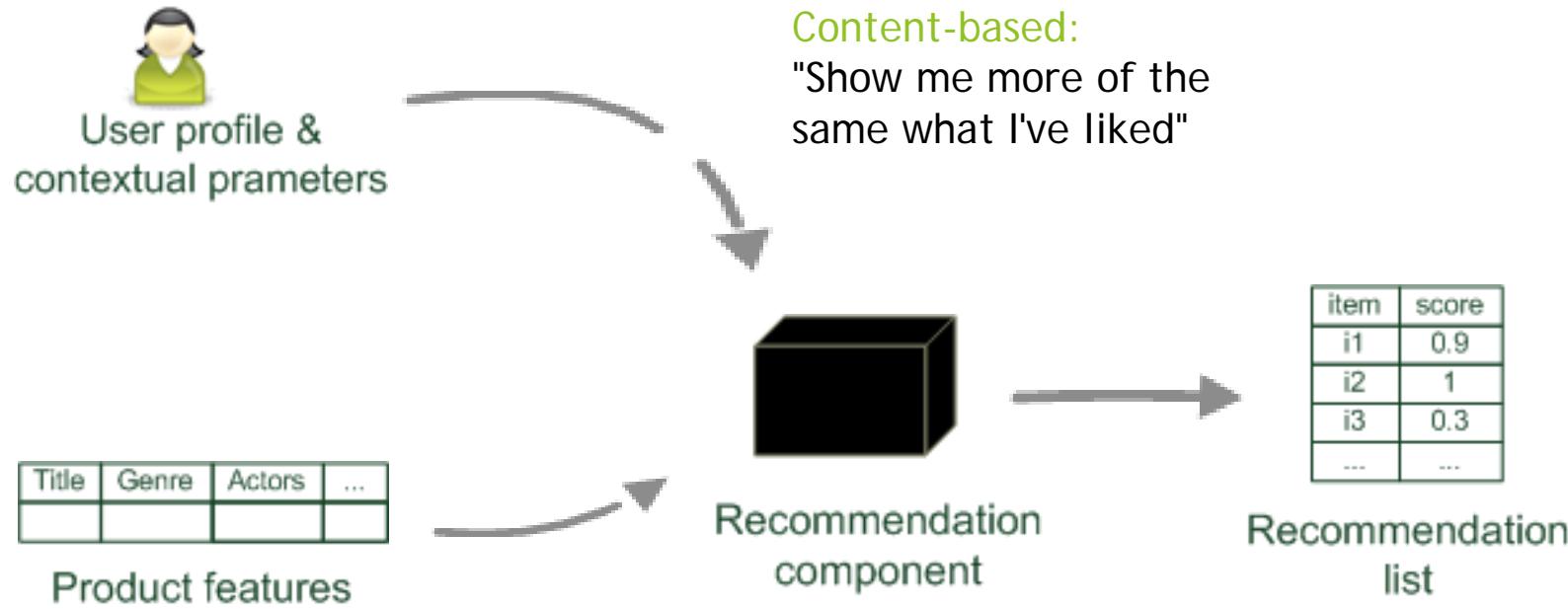
# Recommendation Paradigms



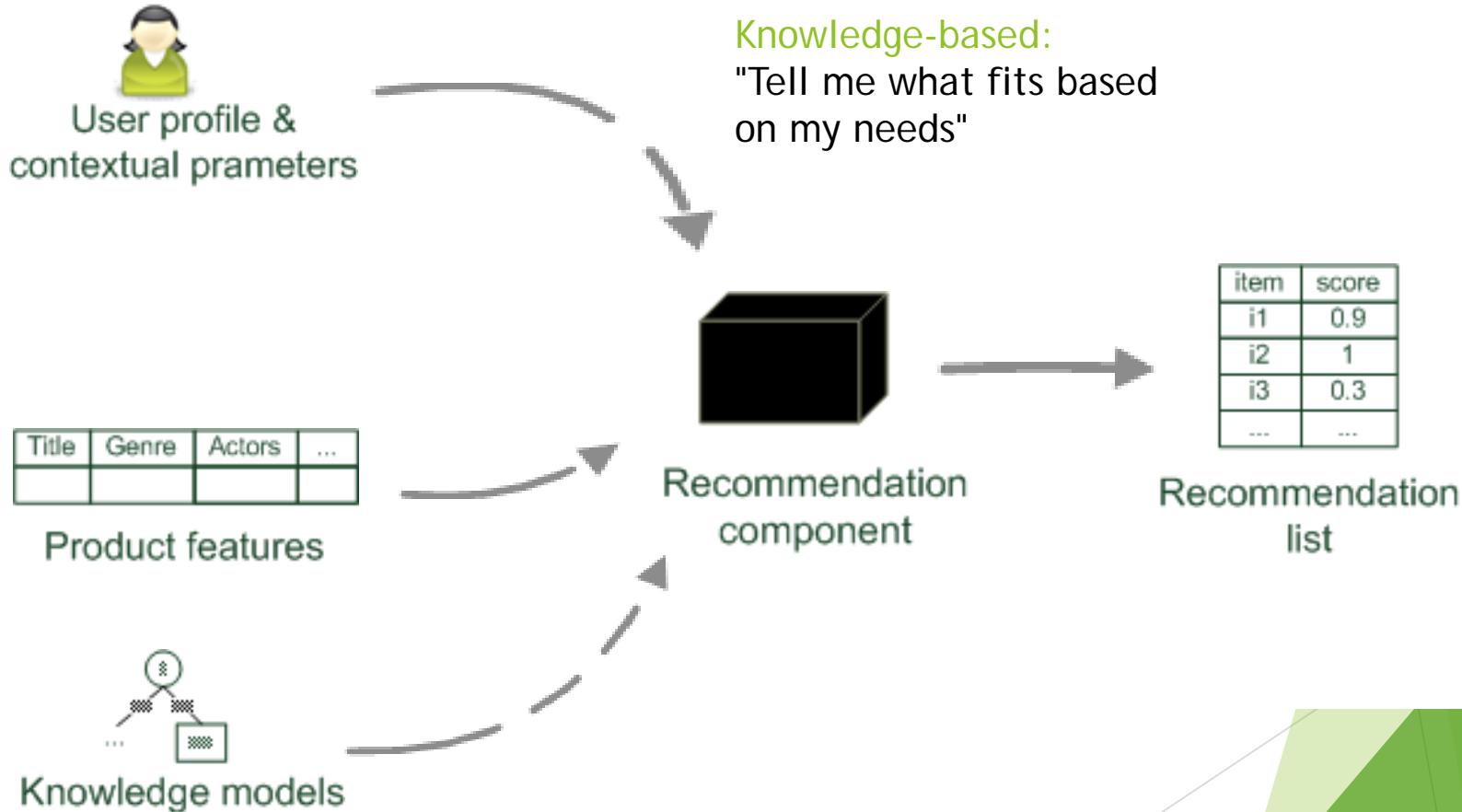
# Recommendation Paradigms



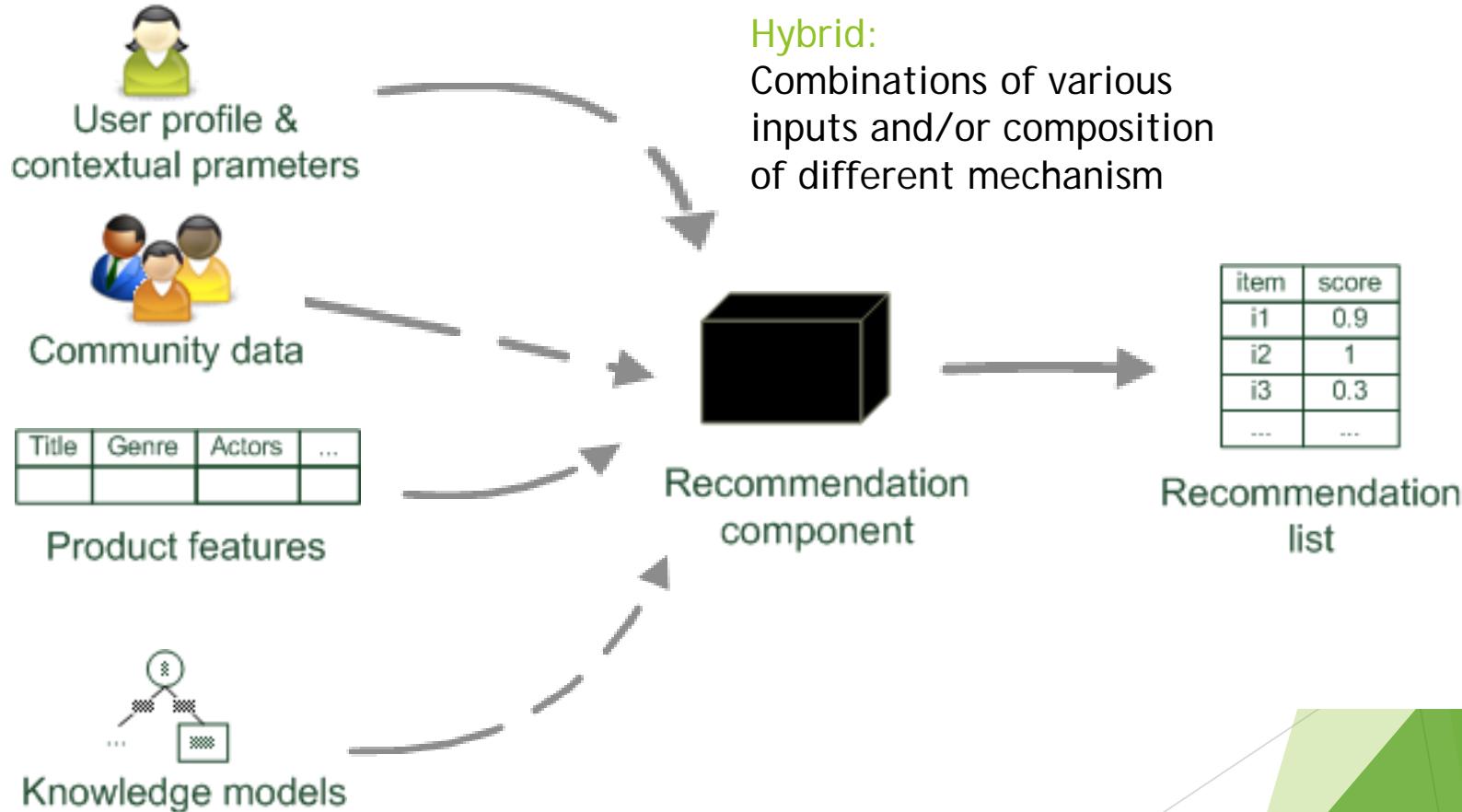
# Recommendation Paradigms



# Recommendation Paradigms



# Recommendation Paradigms



# Collaborative Filtering

- ▶ The most prominent approach to generate recommendations
  - ▶ Used by large commercial e-commerce sites
  - ▶ Well-understood, various algorithms and variations exist
  - ▶ Applicable in many domains
- ▶ Approach
  - ▶ Use the preference patterns of a community to recommend items
  - ▶ One first algorithmic solution
    - ▶ Find users that are similar to the current one
    - ▶ Recommend what these other users liked

# K-Nearest-Neighbors (kNN)

- ▶ A common (academic) problem setup
  - ▶ Given a matrix of explicit or implicit preferences of users for items
  - ▶ Predict the missing cells

	Item1	Item2	Item3	Item4	Item5
Alice	5	3	4	4	?
User1	3	1	2	3	3
User2	4	3	4	3	5
User3	3	3	1	5	4
User4	1	5	5	2	1

# K-Nearest-Neighbors

- ▶ Find k users that are similar to Alice
  - ▶ How many neighbors? How to determine similarity?
- ▶ Use their rating for Item5 to predict Alice's rating
  - ▶ How to combine the ratings?

	Item1	Item2	Item3	Item4	Item5
Alice	5	3	4	4	?
User1	3	1	2	3	3
User2	4	3	4	3	5
User3	3	3	1	5	4
User4	1	5	5	2	1

# Similarity Computation (kNN)

- Using Pearson's correlation coefficient to estimate preference similarity between users

$$sim(a, b) = \frac{\sum_{p \in P} (r_{a,p} - \bar{r}_a)(r_{b,p} - \bar{r}_b)}{\sqrt{\sum_{p \in P} (r_{a,p} - \bar{r}_a)^2} \sqrt{\sum_{p \in P} (r_{b,p} - \bar{r}_b)^2}}$$

	Item1	Item2	Item3	Item4	Item5
Alice	5	3	4	4	?
User1	3	1	2	3	3
User2	4	3	4	3	5
User3	3	3	1	5	4
User4	1	5	5	2	1

sim = 0,85

sim = 0,70

sim = -0,79

# Rating Prediction (kNN)

- ▶ A common prediction function

$$pred(a, p) = \bar{r}_a + \frac{\sum_{b \in N} sim(a, b) * (r_{b,p} - \bar{r}_b)}{\sum_{b \in N} sim(a, b)}$$

- ▶ Takes Alice's average rating into account
- ▶ Takes the similarity degree of the neighbors into account
- ▶ Many variations of this prediction scheme exist
  - ▶ Including an “item-based” approach, where we look for items that received similar ratings

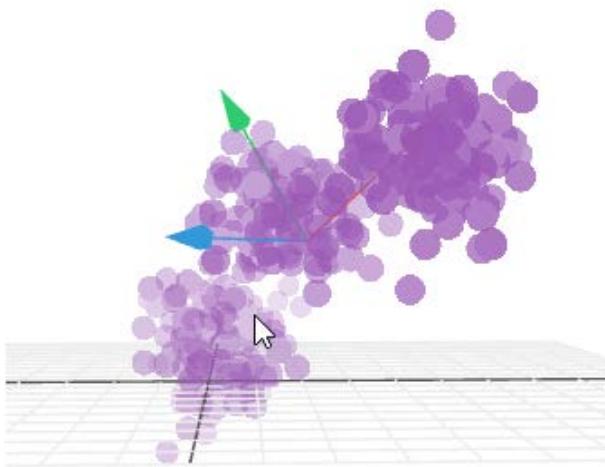
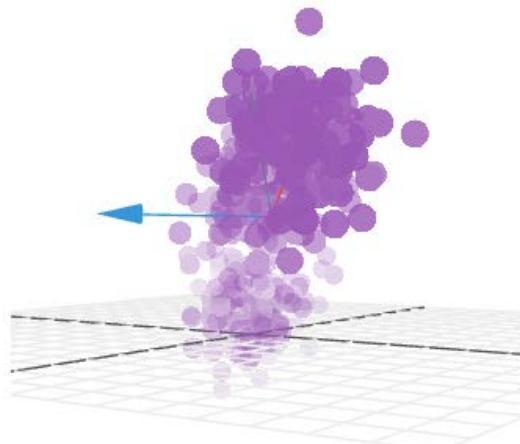
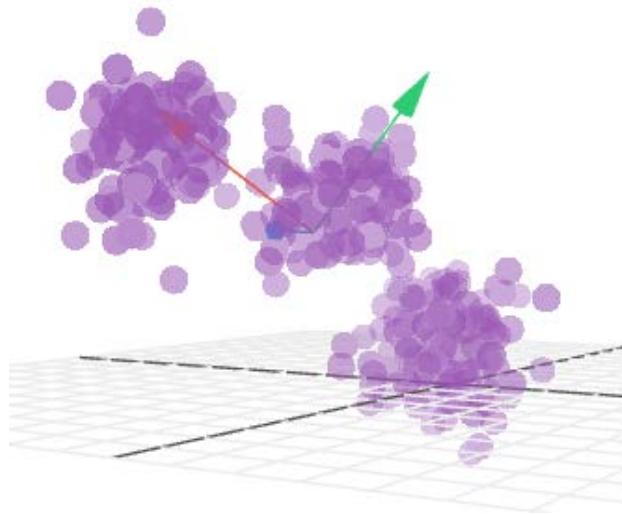
# Generalized Problem

- ▶ Rating prediction (and recommendation) reduces to a matrix completion problem
- ▶ The general optimization problem:
  - ▶ Given a set of noisy rating observations  $(x, y)$ , learn a function  $f(x) = y$  that predicts unknown  $y$  values for a given  $x$ .
  - ▶ Optimization goals: Minimize the prediction error, avoid overfitting to given data
- ▶ A large variety of machine learning approaches to estimate the function were proposed

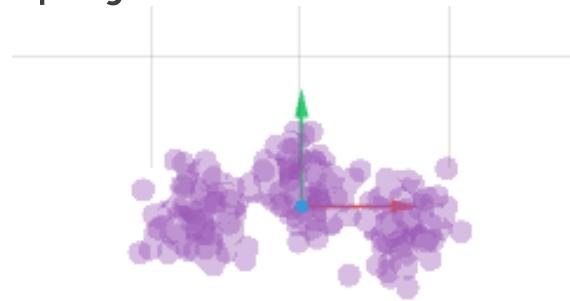
# Matrix Factorization (MF)

- ▶ Became popular during the Netflix Prize competition
- ▶ Adopt ideas of Principal Component Analysis (PCA)
  - ▶ Given a large dataset with values for many and possibly correlated variables
  - ▶ Convert them to a much smaller set of values of linearly uncorrelated variables (principal components)
  - ▶ The first principal component has the largest variance
  - ▶ The next component has the highest variance, but has to be orthogonal to the preceding components (i.e., capture a different aspect).

► 3D - Not much information from certain angles



► Not much information lost in 2D projection



Visualization from <http://setosa.io/ev/principal-component-analysis/>

# Singular Value Decomposition

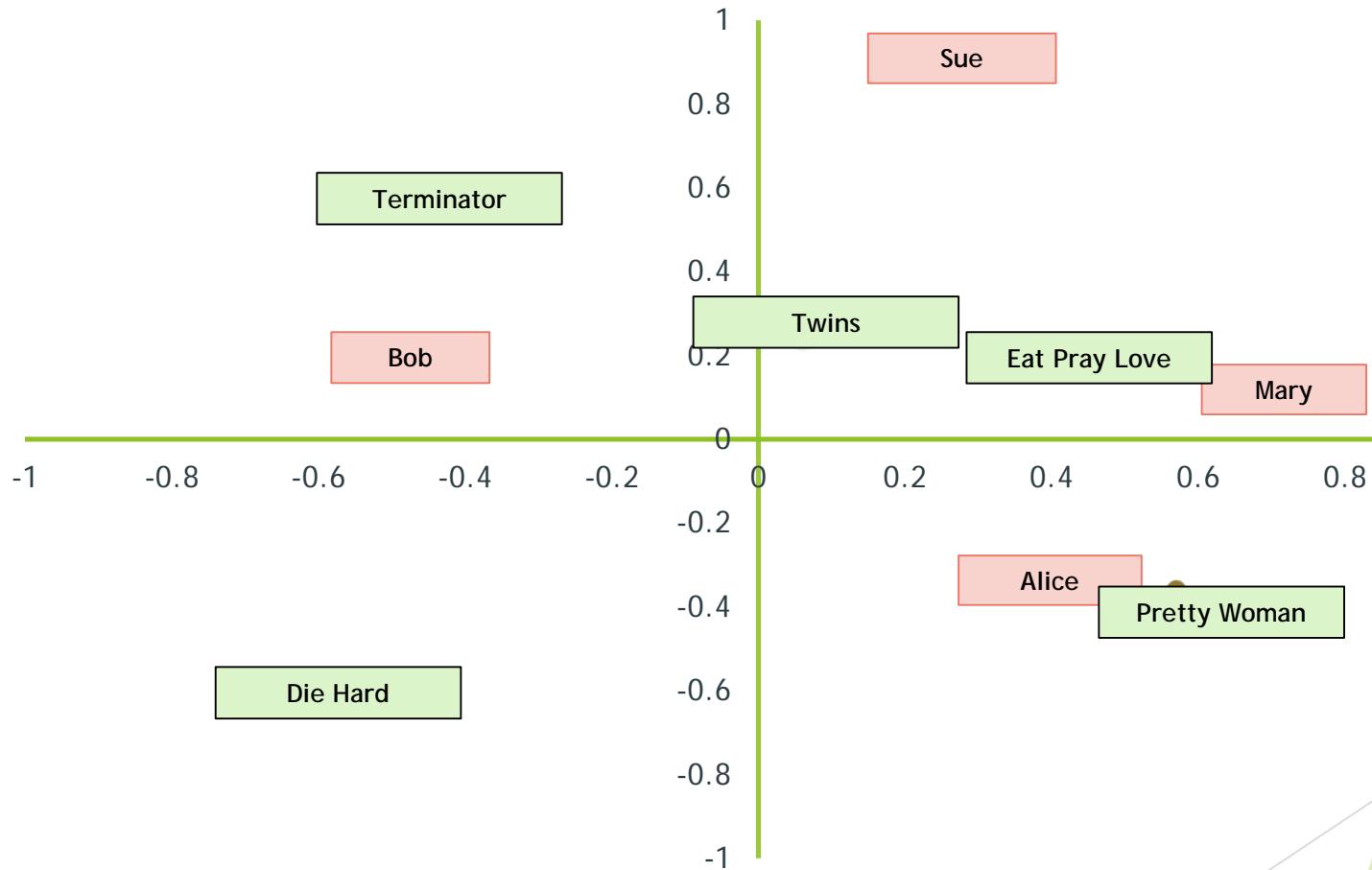
- ▶ Technical approach - Singular Value Decomposition (SVD)

- ▶ Decompose given matrix M as follows

$$M = U \times \Sigma \times V^T$$

- ▶ Only retain the most important signals (largest sing. values)
  - ▶ Original matrix is approximated (removes noise, uncovers latent relationships)

# Projection into 2D Space



- ▶ **Problem:** We do not know what the dimensions are

# Matrix Factorization (MF)

- ▶ In recommender systems
  - ▶ Project users and items in the same “latent space”
- ▶ Technical approach in recommender systems
  - ▶ Use only two-matrix decomposition
  - ▶ Use an iterative approximation approach, e.g., based on gradient descent
  - ▶ Number of latent factors usually set between 50 and 200, to maximize accuracy
  - ▶ Combine with additional factors (biases)
- ▶ Related to Probabilistic Latent Semantic Analysis
  - ▶ Finding latent relationships between concepts in text documents

# SVD-based Recommendation

- U and V correspond to latent user and item vectors

$$M_k = U_k \times \Sigma_k \times V_k^T$$

$U_k$	Dim1	Dim2
Alice	0.47	-0.30
Bob	-0.44	0.23
Mary	0.70	-0.06
Sue	0.31	0.93

$V_k^T$	Terminator	Die Hard	Twins	Eat Pray Love	Pretty Woman
Dim1	-0.44	-0.57	0.06	0.38	0.57
Dim2	0.58	-0.66	0.26	0.18	-0.36

$$\hat{r}_{ui} = \bar{r}_u + U_k(Alice) \times \Sigma_k \times V_k^T(EPL)$$

$$= 3 + 0.84 = 3.84$$

$\Sigma_k$	Dim1	Dim2
Dim1	5.63	0
Dim2	0	3.23

# Collaborative Filtering

## ► Summary

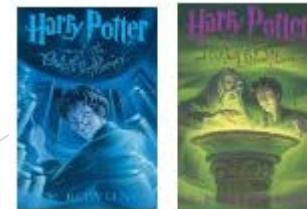
- ▶ Largely used in real-world systems
- ▶ Do not require information about the items or users
- ▶ However, require existence of a user community
- ▶ Many, many algorithms proposed in the literature
  - ▶ Including ones that optimize the ranking and not the predictions
  - ▶ Most learned “models” (in the machine learning sense) cannot be easily interpreted

# Content-based (CB) Filtering

- ▶ Again:
  - ▶ Determine preferences of user based on past behavior
  - ▶ Alternative preference acquisition methods
    - ▶ ask the user, look at recently viewed items
- ▶ This time, however:
  - ▶ Look at what the current user liked (purchased, viewed, ...)
  - ▶ Estimate the user's preference for certain item features
    - ▶ e.g., genre, authors, release date, keywords in the text



Source: Amazon.com



# What is the “Content”?

- ▶ CB-recommendation techniques were often applied to recommend text documents
  - ▶ E.g., web pages or newsgroup message
- ▶ The term content however in many applications refers to meta-data
  - ▶ E.g., the author of a book, the genre of a movie

Title	Genre	Author	Type	Price	Keywords
The Night of the Gun	Memoir	David Carr	Paperback	29.90	Press and journalism, drug addiction, personal memoirs, New York
The Lace Reader	Fiction, Mystery	Brunonia Barry	Hardcover	49.90	American contemporary fiction, detective, historical
Into the Fire	Romance, Suspense	Suzanne Brockmann	Hardcover	45.90	American fiction, murder, neo-Nazism

# Recommendation Approach

- ▶ Represent items and users in the same way

Title	Genre	Author	Type	Price	Keywords
The Night of the Gun	Memoir	David Carr	Paperback	29.90	Press and journalism, drug addiction, personal memoirs, New York
The Lace Reader	Fiction, Mystery	Brunonia Barry	Hardcover	49.90	American contemporary fiction, detective, historical
Into the Fire	Romance, Suspense	Suzanne Brockmann	Hardcover	45.90	American fiction, murder, neo-Nazism

Title	Genre	Author	Type	Price	Keywords
...	Fiction	Brunonia, Barry, Ken Follett	Paperback	25.65	Detective, murder, New York

- ▶ A simple method

- ▶ Compute the similarity of an unseen item with the user profile based on the keyword overlap (Dice coefficient)
- ▶ Or use and combine multiple metrics

$$\frac{2 \times |\text{keywords}(b_i) \cap \text{keywords}(b_j)|}{|\text{keywords}(b_i)| + |\text{keywords}(b_j)|}$$

# TF-IDF Encoding

- ▶ Simple keyword representation has its problems
  - ▶ In particular when automatically extracted:
    - ▶ Not every word has similar importance
    - ▶ Longer documents have a higher chance to have an overlap with the user profile
- ▶ Standard measure: TF-IDF
  - ▶ Encodes text documents in multi-dimensional Euclidian space
    - ▶ Weighted term vector
  - ▶ TF: Measures, how often a term appears
    - ▶ Assuming that important terms appear more often
    - ▶ Normalization has to be done in order to take document length into account
  - ▶ IDF: Aims to reduce the weight of terms that appear in all documents

# Recommendation Approach

- ▶ Simple method
  - ▶ Every item is a vector of terms
  - ▶ Take the n most liked items of the user, compute an averaged TF-IDF vector
  - ▶ Compare this profile vector with all recommendable items
    - ▶ Use the cosine similarity as a similarity (distance) measure
  - ▶ Recommend the most similar items

# Content-based Filtering

## ► Summary

- Additional information about the items can be exploited (but must exist)
- No large user community required
- Recommends “more of the same”, no surprises

# Knowledge-based Approaches

- ▶ Suitable for high-involvement items (cars, mobiles)
  - ▶ Cannot be based on few ratings alone, as too many details matter
  - ▶ Explicit and detailed preferences of the user
    - ▶ "The color of the car should be black"
  - ▶ More elaborate interaction mechanisms required
    - ▶ Conversational strategy needed



How do you rate your expertise in the domain?

I am a new to this. ?

I already know the basic terms ?

I am the expert. ?

**Why this question**

Search now

Glossary

Quick search

Start over

Go back Continue

# Critiquing

- ▶ An intuitive knowledge-based recommendation method
- ▶ Navigate the product space by "criticizing" the current solution
- ▶ Example:
  - ▶ Looking for a restaurant ...
- ▶ Knowledge types:
  - ▶ About items
  - ▶ Adaptation step sizes
  - ▶ (Similarity functions)

The screenshot shows a user interface for finding a favorite restaurant. At the top, it says "find your favourite restaurant". Below that, there's a cloud icon.

**In Vienna you chose:**

**Biergasthof**

+43 1 123 123 123  
Mariahilferstrasse 123,  
1010 Wien

30€-50€  
Local cuisine

local food, central in the city, weekend brunch, room with a view,  
famous for beer, seasonal dishes, group bookings, open all day

**For Graz we recommend:**

**Brauhof**

+43 316 45 45 45  
Brauhofstrasse 45,  
8023 Graz

30€-50€  
Local cuisine

local food, own beer, weekend lunch, open all day, private function room,  
famous for beer, seasonal dishes, group bookings, good transport connection

Less \$\$      Nicer      Cuisine      More Quiet

Traditional      Creative      Livelier

# Knowledge-based Approaches

- ▶ Selection and ranking of items based on explicit knowledge
  - ▶ About user preferences
  - ▶ About item characteristics
  - ▶ About how to match user preferences with items
    - ▶ E.g., If user prefers luxury brands, only recommend items of manufacturers X, Y, and Z.
- ▶ Technical approaches
  - ▶ Constraints, rules, utility functions, case-based reasoning

# Example software: Advisor Suite

**CW Advisor Designer**

File Edit Settings Help

Advisor applications

- Pension Advisor
- Investment Advisor
  - Default client
  - Product properties
- Customer properties
  - All
    - availability\_of\_funds
    - advisory\_wanted
    - direct\_product\_search
    - duration\_of\_investment
    - knowledge\_level
    - type\_high\_risk\_investment
    - type\_low\_risk\_investment
    - willingness\_to\_take\_risks
  - Product selection
  - Dialogue hints
  - Derivations
  - Utility definition
  - Process Designer
- Test Designer
- Analysis
- Administrative
- Global customer

Designing test cases

Designing recommender processes

Main window

Recommender applications (financing, investment, ...)

Product properties (name, investment period, ...)

Constraint (incompatibility)

Name: willingness\_to\_take\_risks\_investment\_period  
Description: A high willingness to take risks is incompatible with short investment periods.  
internal description: Short investment periods should be avoided in combination with high risk products!  
explanation for user: willingness\_to\_take\_risks = "high" AND duration\_of\_investment = NULL  
Answers:

- Customer properties ► "mediumterm"
- "longterm"

Properties

Incompatibility

The screenshot shows the CW Advisor Designer application window. On the left is a tree view of advisor applications, with 'Investment Advisor' expanded to show 'Default client', 'Product properties', and 'Customer properties'. Under 'Customer properties', there's a list of properties like 'availability\_of\_funds' and 'willingness\_to\_take\_risks'. The main area has tabs for 'Main window', 'Designing test cases', and 'Designing recommender processes'. A central dialog box is titled 'Constraint (incompatibility)' and contains a table with columns 'Name', 'Description', 'Explanation', and 'Rule'. The 'Name' field is 'willingness\_to\_take\_risks\_investment\_period'. The 'Description' field contains the text 'A high willingness to take risks is incompatible with short investment periods.' Below it, the 'Explanation' field contains 'Short investment periods should be avoided in combination with high risk products!'. The 'Rule' field shows the logical expression 'willingness\_to\_take\_risks = "high" AND duration\_of\_investment = NULL'. A dropdown menu under 'Answers' shows two options: 'Customer properties ► "mediumterm"' and '"longterm"'. Callout boxes point from various parts of the interface to these specific elements.

# Rules used for explanations

The screenshot shows a web-based application for 'VIBE - the virtual adviser for the Warmbad-Villach spa resort'. At the top, there's a navigation bar with links for 'HOME', 'CALL BACK SERVICE', and 'RECOMMENDATION'. On the left, a woman in a red dress is pointing upwards. A speech bubble next to her contains the text: 'You're bound to ask yourself why I recommended the following. I'll be happy to explain...'. To the right, a box titled 'My arguments specially for you.' lists several points:

- I am happy to have found autumn packages for you, as you wished.
- If you want more suggestions for a specific date, you'll have to use the detailed advice option (more questions).
- We have a whole range at the Warmbad-Villach spa resort to suit your request Leisure and activities programme & Long walks. Ask about them.
- Our comprehensive supporting programme of cultural events (Carinthian Summer Music Festival, Villach Carnival, exhibitions at the Warmbad culture club, Jazz Over Villach, etc.) all year round and attractions in the vicinity will round off your stay at the
- Do you want to feel fit and healthy? Our sports and activities programmes respond to your wishes

At the bottom left, the word 'Fertig' is visible, and at the bottom right, there are 'Back' and 'Next' buttons.

# Hybrid Approaches

- ▶ Collaborative filtering, content-based filtering, knowledge-based recommendation
  - ▶ All pieces of information can be relevant in real-world recommendation scenarios, but all may have shortcomings
- ▶ Hybrid: Combine two or more approaches
  - ▶ Avoid some of the shortcomings
  - ▶ Different hybridization designs
    - ▶ Monolithic exploiting different features
    - ▶ Parallel use of several systems
    - ▶ Pipelined invocation of different systems

# Summary

- ▶ Presented basic approaches to build recommender systems
  - ▶ Collaborative filtering, content-based filtering, knowledge-based approaches, hybrids
- ▶ Recommender systems operate on the basis of different types of data
  - ▶ Ratings
  - ▶ Information about items
  - ▶ Learned models of different complexities
  - ▶ Inference knowledge ...
- ▶ These aspects determine which types of user interactions can be (easily) supported

# Where are we?

09:00 - 09:45

- ▶ Introduction & Background



09:45 - 10:14

- ▶ Interacting recommender systems - A review (Part I)

10:15 - 10:45

- ▶ Coffee break

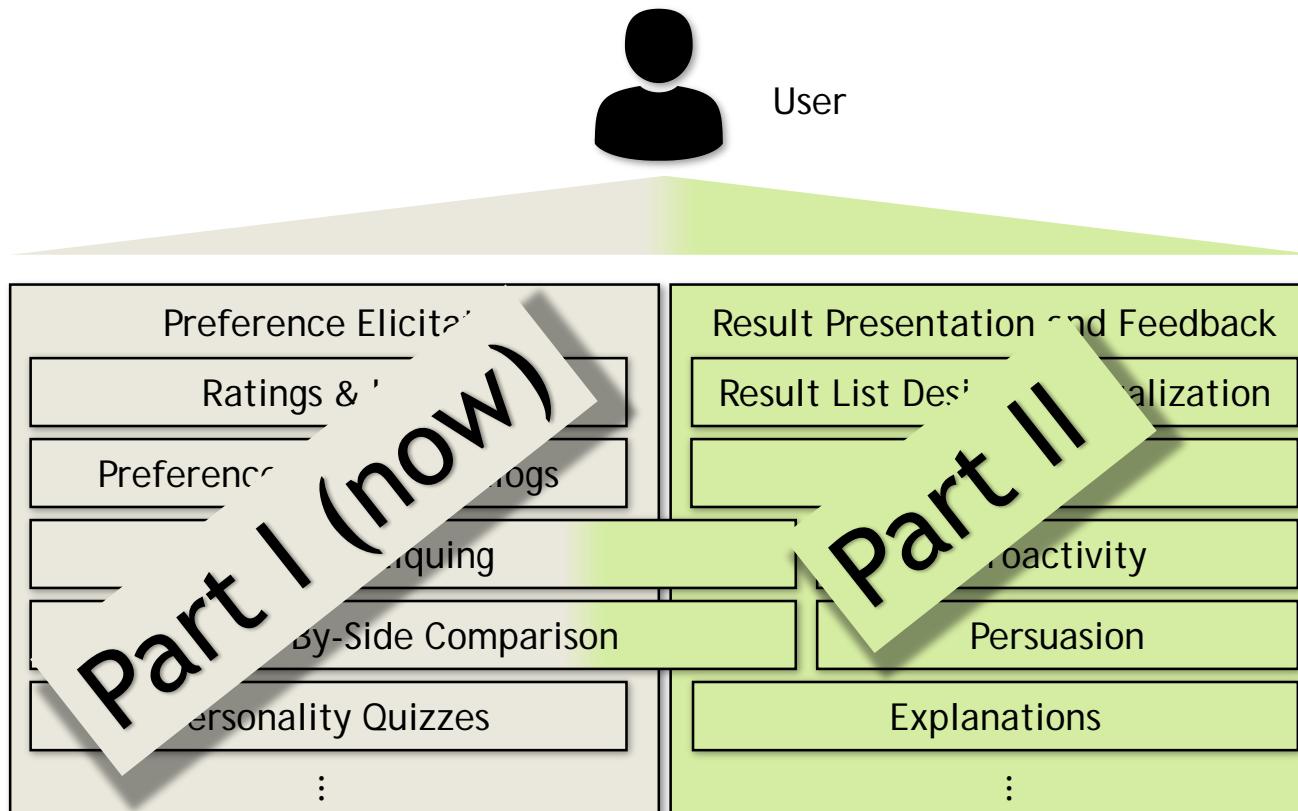
10:45 - 11:15

- ▶ Interacting recommender systems - A review (Part II)

11:15 - 12:15

- ▶ Explanations in recommender systems
- ▶ Discussion

# Overview



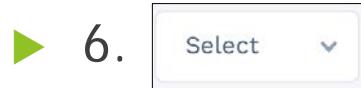
Recommender System

# Interacting with Recommender Systems

Part I: Interactions during  
Preference Elicitation

# Exercise

- ▶ What methods do you prefer to input your preferences?



# User Preference Elicitation

- ▶ Methods to ...
  - ▶ let users express their tastes
  - ▶ acquire a user profile  
or guide users directly to the “right item”
- ▶ Requirements
  - ▶ Must not be tedious -> keep users interested!
  - ▶ As much useful information as possible  
in as few interaction steps as possible
  - ▶ Fun, engagement, basis of trust, reliability, ...

# Topics of This Session

- ▶ Explicit ratings and likes
- ▶ Preference forms and dialogs
- ▶ Critiquing
- ▶ Alternative elicitation techniques
  - ▶ Side-by-side comparison between items
  - ▶ Picture-based/tag-based elicitation
  - ▶ Personality quizzes

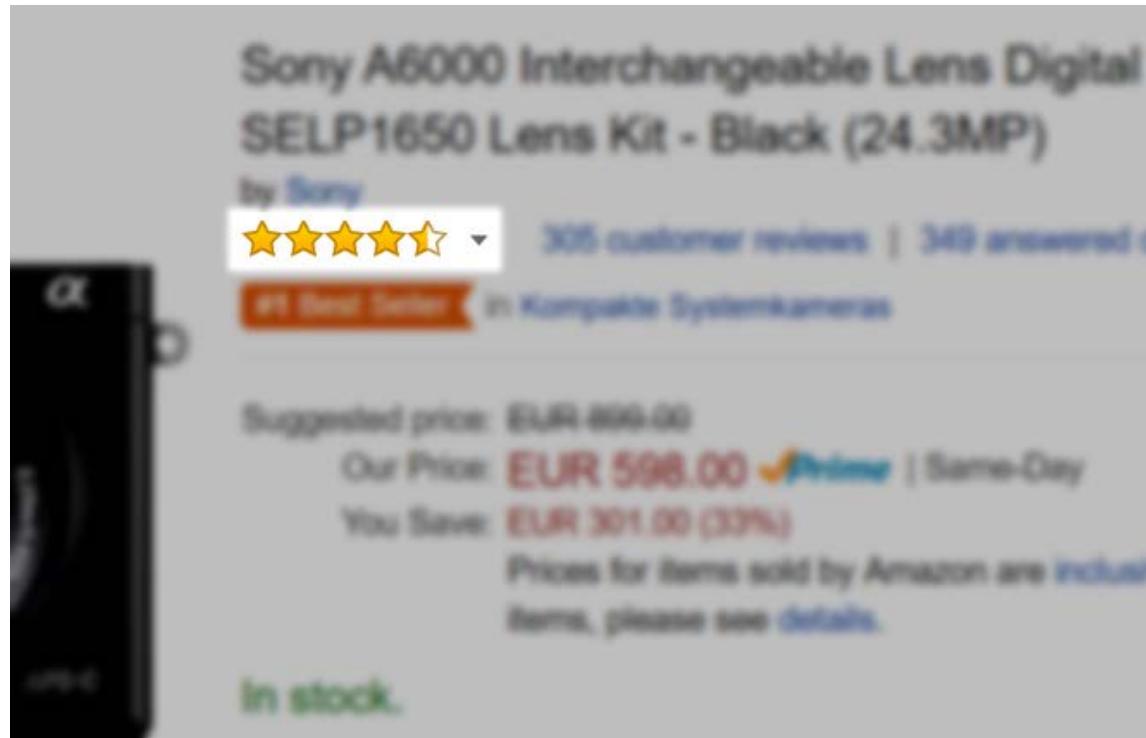
# Explicit Ratings and Likes

# Explicit Ratings and Likes

- ▶ Our definition: Deliberate user interactions to tell the system about the preference toward an item
- ▶ Many approaches assume that ratings/likes are readily available
- ▶ But in reality, many problems arise:
  - ▶ Types of user input
  - ▶ User effort
  - ▶ Data reliability/granularity
  - ▶ Cold-start

# Feedback Scale

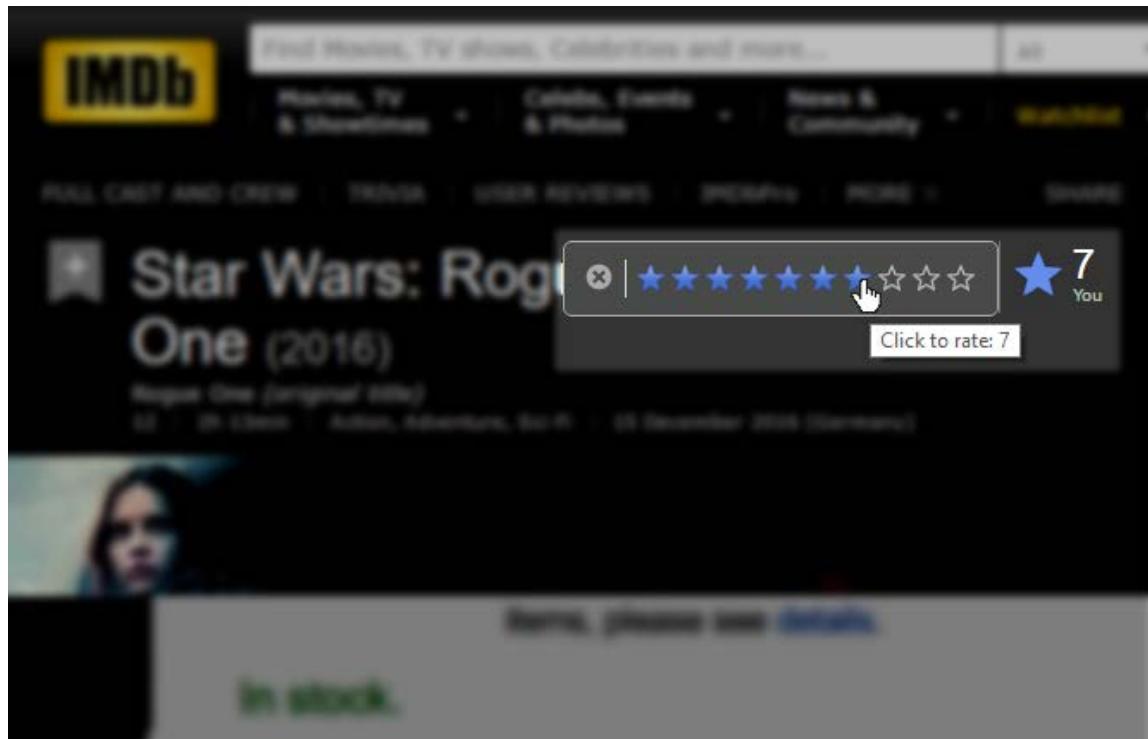
- ▶ How to make it as easy as possible to express taste?
- ▶ Common approaches:



Source: amazon.com

# Feedback Scale

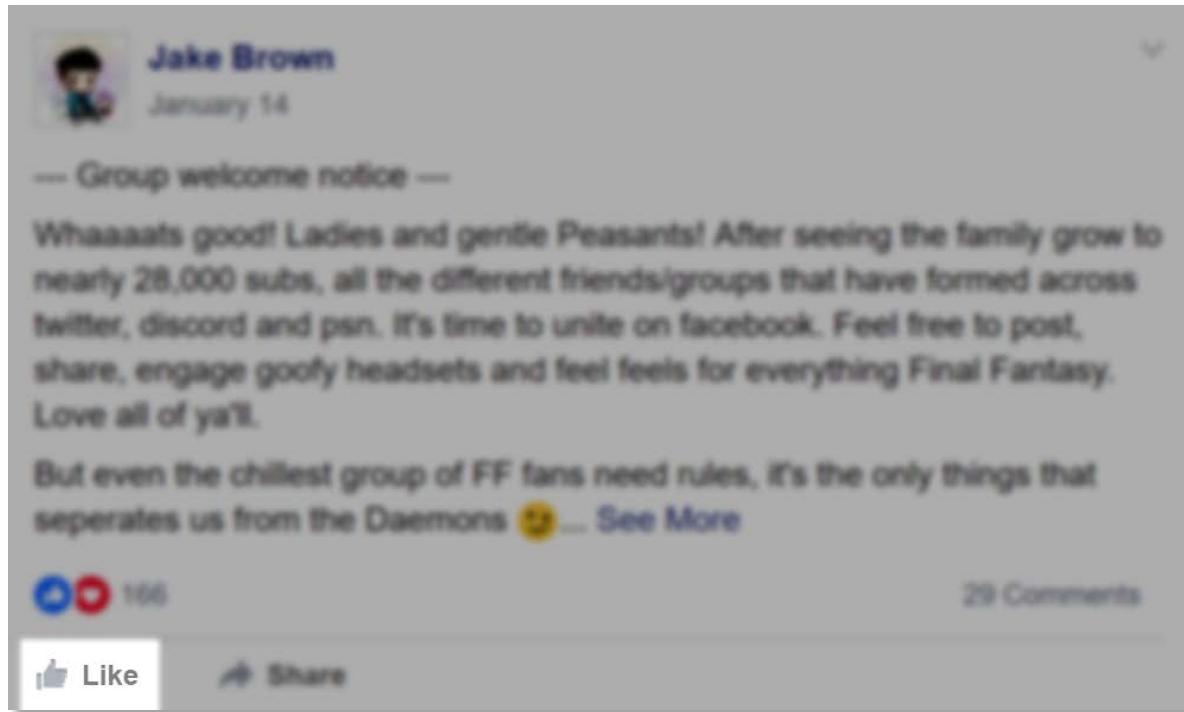
- ▶ How to make it as easy as possible express taste?
- ▶ Common approaches:



Source: [imdb.com](https://www.imdb.com)

# Feedback Scale

- ▶ How to make it as easy as possible express taste?
- ▶ Common approaches:



Source: facebook.com

# Feedback Scale

- ▶ How to make it as easy as possible express taste?
- ▶ Not-so-common approaches (from the literature):

First rate two jokes.

Q: If a person who speaks three languages is called "trilingual," and a person who speaks two languages is called "bilingual," what do you call a person who only speaks one language?

A: American!

Less Funny                          More Funny

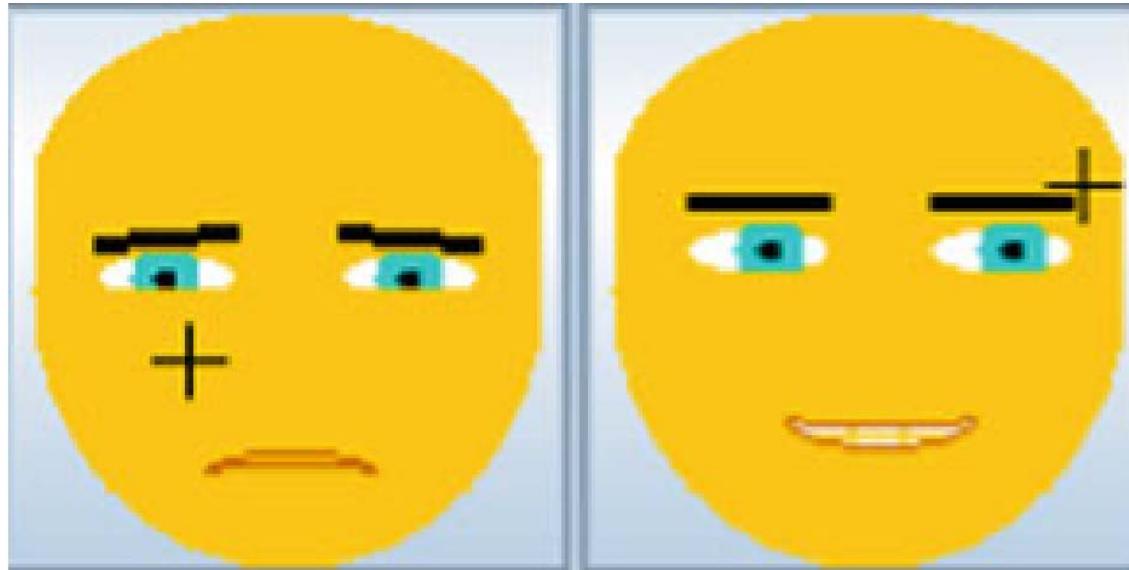


Next

Source: [1]

# Feedback Scale

- ▶ How to make it as easy as possible express taste?
- ▶ Not-so-common approaches (from the literature):



Source: [1]

[1] Alina Pommeranz, Joost Broekens, Pascal Wiggers, Willem-Paul Brinkman, and Catholijn M. Jonker. 2012. Designing interfaces for explicit preference elicitation: a user-centered investigation of preference representation and elicitation process. *User Modeling and User-Adapted Interaction* 22, 4 (2012), 357-397.

# Feedback Scale – Considerations

- ▶ Number of options
  - ▶ ★★★★★ vs. ★★★★★★★★ vs.   vs.  Like
- ▶ Wording of possible feedback values
  - ▶ e.g. “bad … very good” vs. “terrible … excellent”
- ▶ Extreme values
  - ▶ “(0) … (10)” vs. “(-5) … (5)”
- ▶ Presence of a neutral option
  - ▶ “(1) (2) (3) (4) (5)” vs. “(1) (2) (3) (4)”
- ▶ Often not considered in study setups

# Feedback Scale – Observations

- ▶ Finer scales -> sense of control
  - ▶ More precision but more effort?
- ▶ Continuous sliders -> blurred boundaries -> less effort
- ▶ Mobile scenarios: different requirements
  - ▶ Reduce functionality? Make everything bigger?
- ▶ In the literature: Little consideration about how data is acquired, despite pitfalls

# Explicit ratings – Reliability

- ▶ Even explicit ratings are only reliable to a degree
  - ▶ Can users rate consistently (over time)?
  - ▶ Feedback directly after consumption or later?
  - ▶ Community rating: Help or bias?



Source: youtube.com

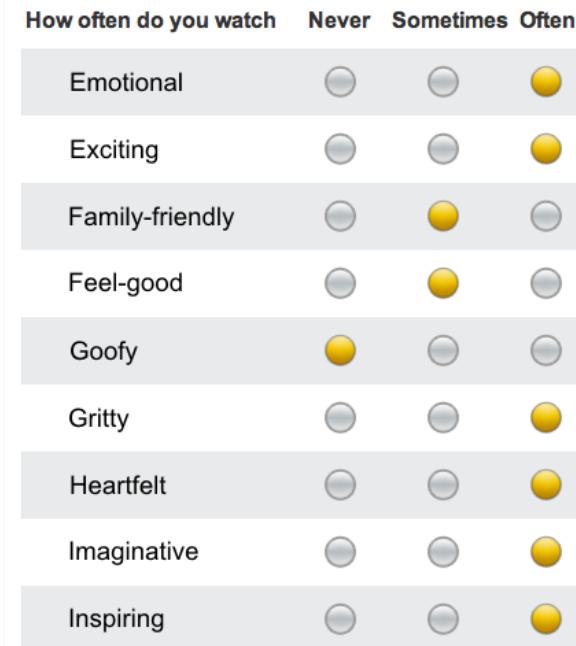
# Explicit ratings – Reliability

- ▶ Even explicit ratings are only reliable to a degree
  - ▶ Can users rate consistently (over time)?
  - ▶ Feedback directly after consumption or later?
  - ▶ Community rating: Help or bias?
  - ▶ Public rating scales
    - ▶ Users become critics
    - ▶ Users like to rate “good” stuff -> 5 stars dominate

# Dealing with Cold-Start Users

- ▶ New user -> reduce entry barrier!
- ▶ Interaction strategies even more important
  
- ▶ Simply monitor users: Trust?
- ▶ Ask users about their tastes
  - ▶ How many questions?  
Trust/accuracy vs. effort
- ▶ Force users to rate items upfront
  - ▶ Same problem: How many items?

## Taste Preferences



Source: netflix.com

# Helping Users to Rate

- ▶ How to reduce rating effort for users?
- ▶ Help users to understand the item



Source: [1]

[1] Tien T. Nguyen, Daniel Kluver, Ting-Yu Wang, Pik-Mai Hui, Michael D. Ekstrand, Martijn C. Willemsen, and John Riedl. 2013. Rating support interfaces to improve user experience and recommender accuracy. In *Proceedings of the 7th Conference on Recommender Systems (RecSys '13)*. 149-156.

# Helping Users to Rate

- ▶ How to reduce rating effort for users?
- ▶ Help users to understand the item
- ▶ Suggest items to rate vs. let users search themselves?
  - ▶ Suggestions seem to be easier/more reliable
  - ▶ Self-selection seems to lead to higher user satisfaction

# Other Explicit Rating Interactions

- ▶ Multi-criteria ratings
  - ▶ More effort for users?
  - ▶ Added benefit? For users?  
For the system?
- ▶ Plain text item reviews
  - ▶ Rarely used
  - ▶ How to exploit?

The screenshot shows a user interface for rating a hotel. At the top, there are three questions with 'Yes', 'No', and 'Not Sure' buttons:

- Is the price of this hotel **mid-range?**
- Does this hotel have **paid internet?**

Below these is a section titled "Hotel Ratings" with three items:

- Service: Five circular rating slots followed by a green "Click to rate" button.
- Cleanliness: Five circular rating slots followed by a green "Click to rate" button.
- Sleep Quality: Five circular rating slots followed by a green "Click to rate" button.

Source: tripadvisor.com

★★★★★ Excellent for beginners. A few suggestions on accessories.

By Adam P. on February 20, 2017

Color: Black | Style: w/ 18-55mm | Configuration: Base | **Verified Purchase**

Great camera, I purchased this mainly to take action shots of my dog. Luckily I purchased this around Black Friday and it was considerably cheaper than the normal selling price. I love this camera, I have no issues using it and by exporting the images as RAW format I am able to do post-processing in Adobe Softwares (i.e. Photoshop, Lightroom).

I am by no means a pro photographer, simply someone who reads information online and then tries to go out and take pictures. Attached as some pictures I have taken as-is (i.e. no post-processing).

Source: amazon.com

# Preference Forms and Dialogs

# Preference Forms

- ▶ Often used for cold-start users (on streaming sites)
- ▶ Sometimes available to the whole user base

## Taste Preferences

How often do you watch	Never	Sometimes	Often
Emotional	<input type="radio"/>	<input type="radio"/>	<input checked="" type="radio"/>
Exciting	<input type="radio"/>	<input type="radio"/>	<input checked="" type="radio"/>
Family-friendly	<input type="radio"/>	<input checked="" type="radio"/>	<input type="radio"/>
Feel-good	<input type="radio"/>	<input checked="" type="radio"/>	<input type="radio"/>
Goofy	<input checked="" type="radio"/>	<input type="radio"/>	<input type="radio"/>
Gritty	<input type="radio"/>	<input type="radio"/>	<input checked="" type="radio"/>
Heartfelt	<input type="radio"/>	<input type="radio"/>	<input checked="" type="radio"/>
Imaginative	<input type="radio"/>	<input type="radio"/>	<input checked="" type="radio"/>
Inspiring	<input type="radio"/>	<input type="radio"/>	<input checked="" type="radio"/>

Source: netflix.com

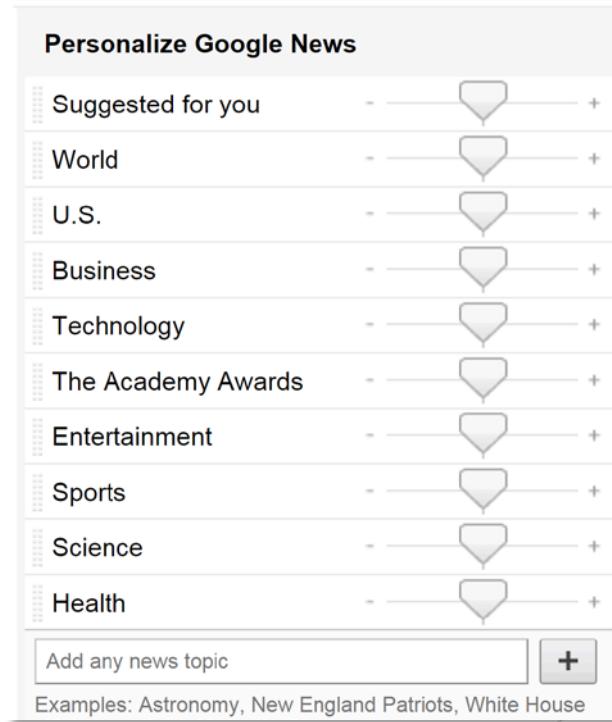
## Personalize Google News

Suggested for you	-	+
World	-	+
U.S.	-	+
Business	-	+
Technology	-	+
The Academy Awards	-	+
Entertainment	-	+
Sports	-	+
Science	-	+
Health	-	+
Add any news topic	<input type="text"/>	<input type="button" value="+"/>
Examples: Astronomy, New England Patriots, White House		

Source: news.google.com

# Preference Forms

- ▶ Often used for cold-start users (on streaming sites)
- ▶ Sometimes available to the whole user base
  
- ▶ User in control
- ▶ But ...
  - ▶ Maybe too complex?
  - ▶ Will users tweak their profiles over time?
  - ▶ What if users mess around too much?
    - ▶ Fallbacks?
    - ▶ Undo option?



Source: news.google.com

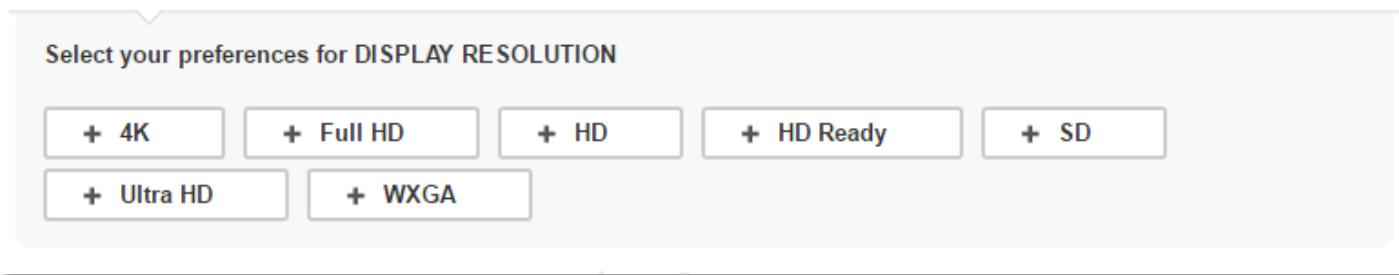
# Conversational Recommenders

- ▶ Mostly for high-involvement products  
(e.g., cameras, TVs, smartphones, ...)
- ▶ Idea:
  - ▶ Ask the user questions and evaluate answers  
(step by step)
  - ▶ In the end, recommend one (or more) items

Select your preferences for DISPLAY RESOLUTION

+ 4K    + Full HD    + HD    + HD Ready    + SD

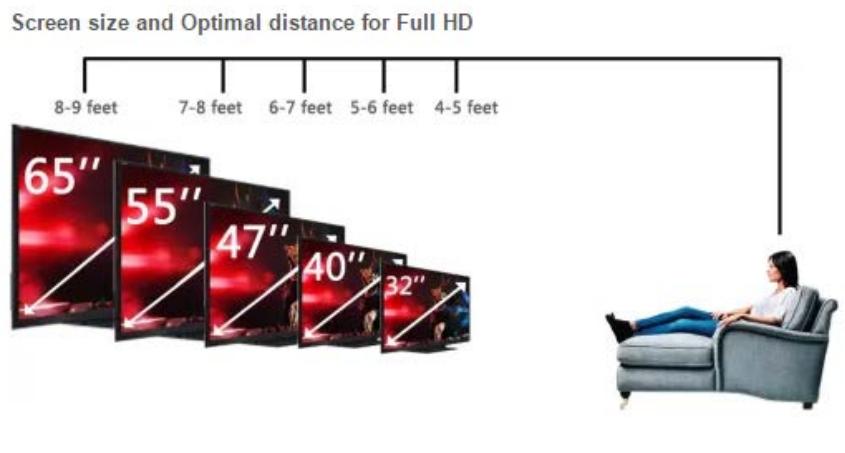
+ Ultra HD    + WXGA



Sources: flipkart.com

# Conversational Recommenders

- User guidance possible:



Source: flipkart.com

Select your preferences for SCREEN SIZE

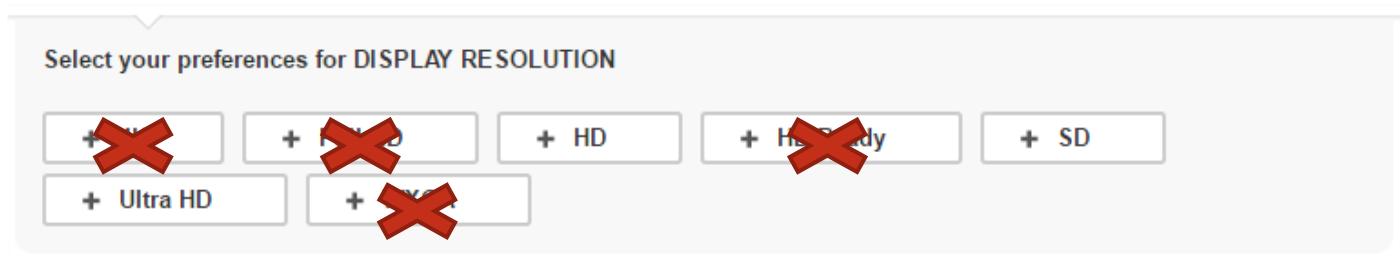
+ 21 & Below   + 22 - 24   + 25 - 31   + 32   + 33 - 42

**x 43 - 54**   + 55 & Above

Source: flipkart.com

# Conversational Recommenders

- ▶ Problems in comparison to other approaches:
  - ▶ Domain-specific knowledge needed
  - ▶ Complex implementation/maintenance
  - ▶ No long-term profiles
- ▶ Open questions:
  - ▶ How to deal with conflicting user requirements?
  - ▶ One-size-fits-all vs. personalization to expertise?

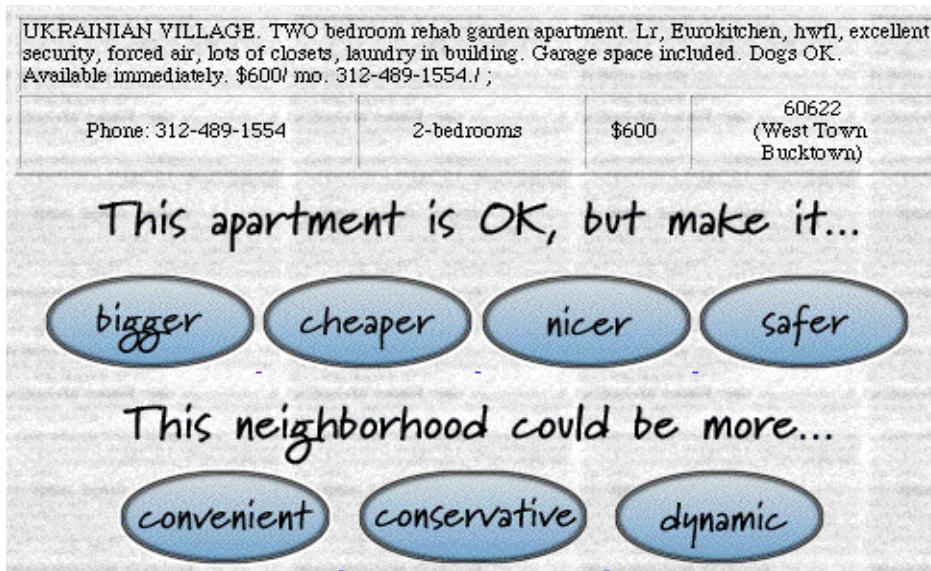


Source: flipkart.com

# Critiquing

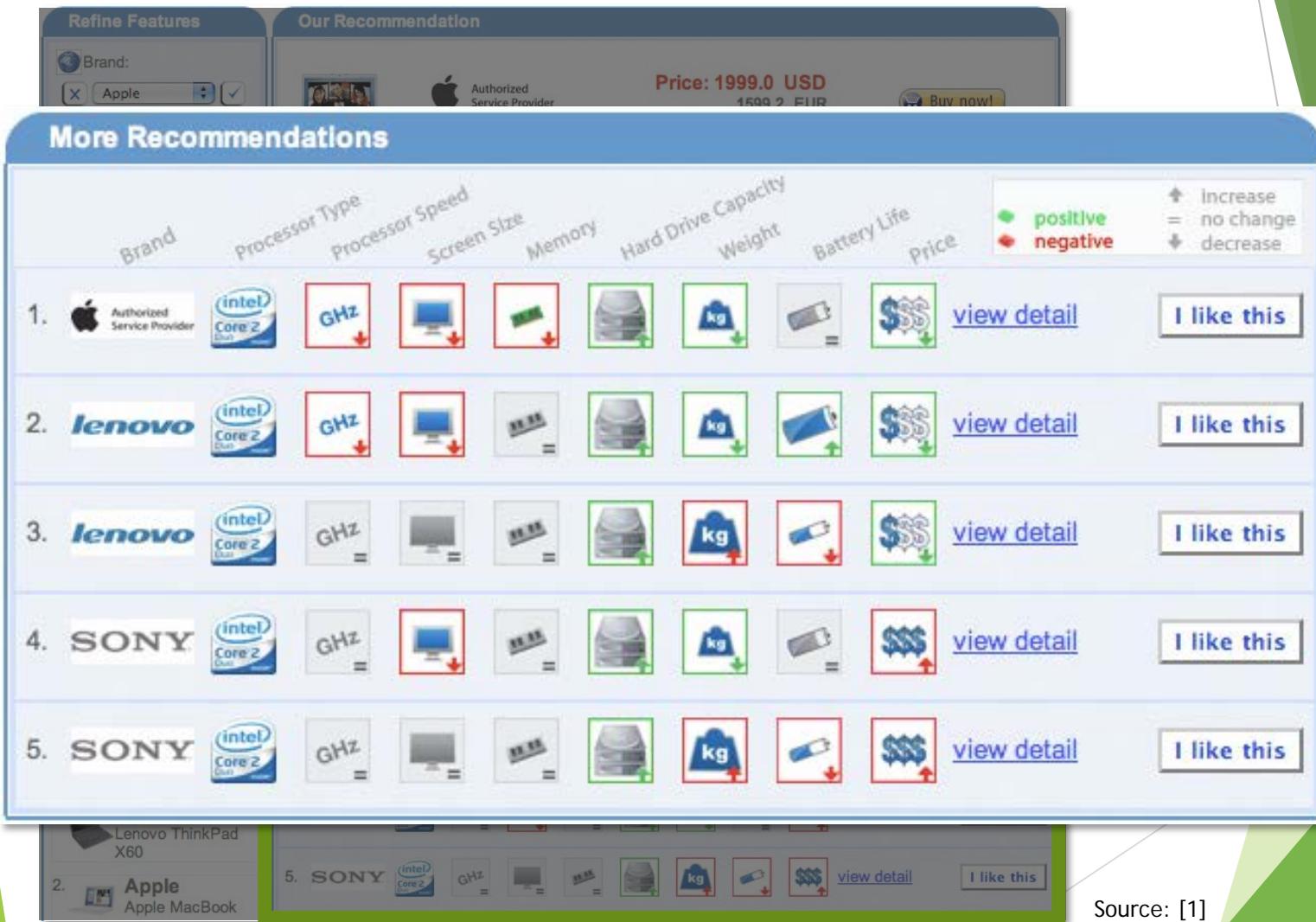
# Critiquing

- ▶ Similar to conversational recommendation
- ▶ But: display a recommendation as soon as possible
- ▶ Let user critique the recommendations until a satisfying option is found



Source: [1]

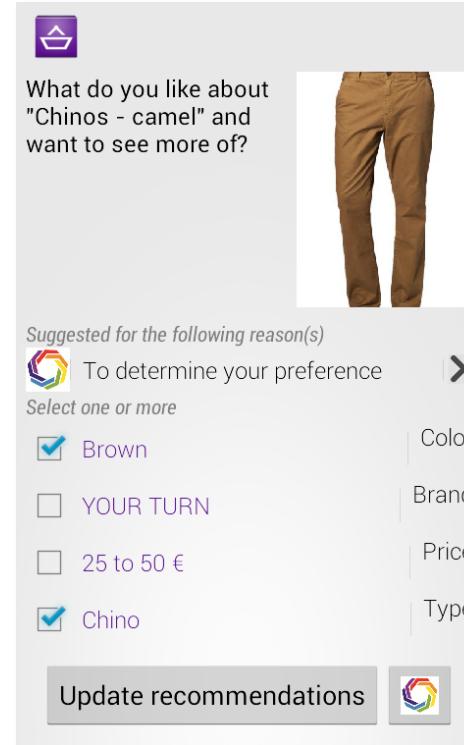
# Compound Critiques



Source: [1]

# Critiquing – Open Questions

- ▶ On mobile?
- ▶ Weighting criteria differently?
- ▶ Integrate preferences into long-term user models?
- ▶ Natural language?
- ▶ How to evaluate offline?



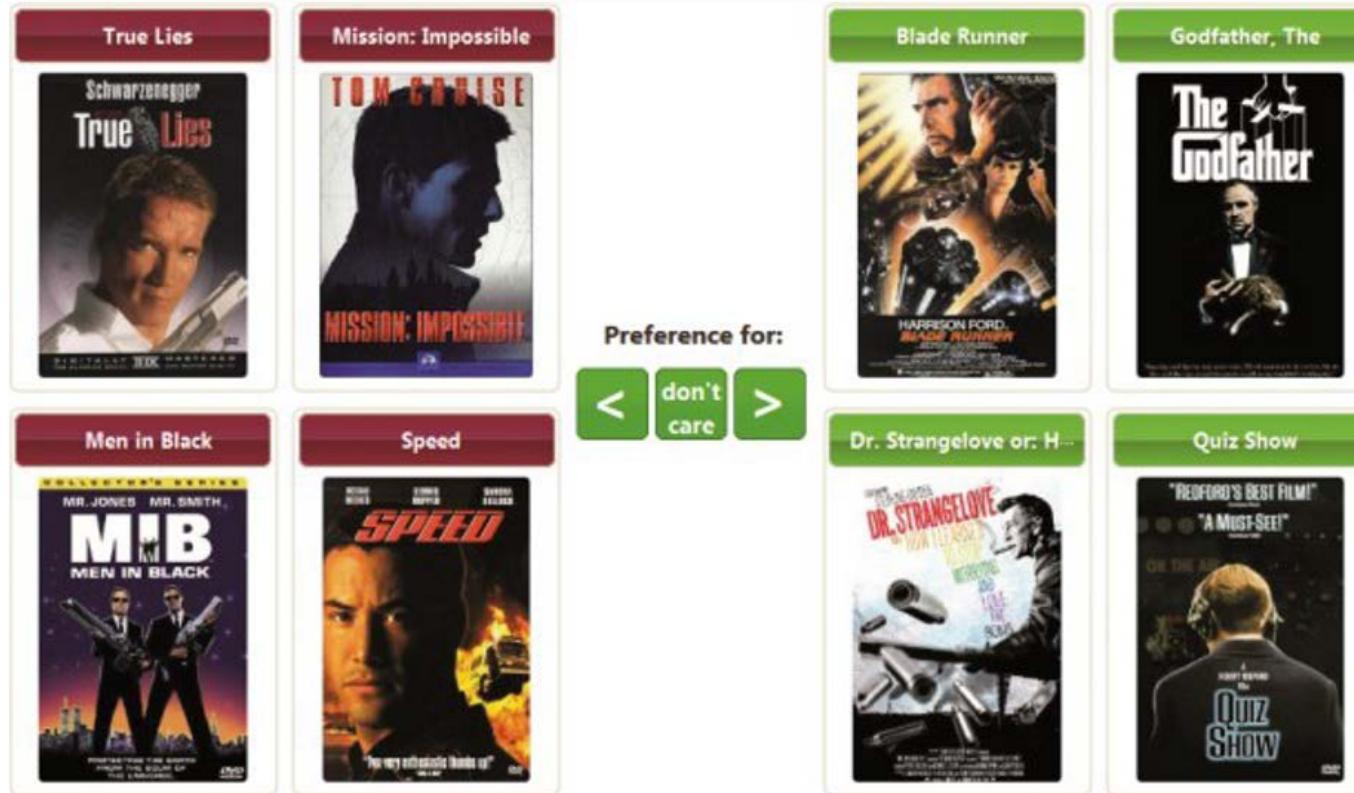
Source: [1]

[1] Béatrice Lamche, Yannick Rödl, Claudius Hauptmann, and Wolfgang Wörndl. 2015. Context-Aware Recommendations for Mobile Shopping. In *Proceedings of the Workshop on Location-Aware Recommendations (LocalRec '15) co-located with the 9th Conference on Recommender Systems (RecSys '15)*. 21-27.

# Alternative Elicitation Techniques

Side-By-Side Comparison, Personality Quizzes,  
Picture-Based, ...

# Alternative Elicitation Techniques: Side-By-Side Comparison of Sets



Source: [1]

[1] Benedikt Loepp, Tim Hussein, and Jürgen Ziegler. 2014. Choice-based preference elicitation for collaborative filtering recommender systems. In *Proceedings of the 2014 SIGCHI Conference on Human Factors in Computing Systems (CHI '14)*. 3085-3094.

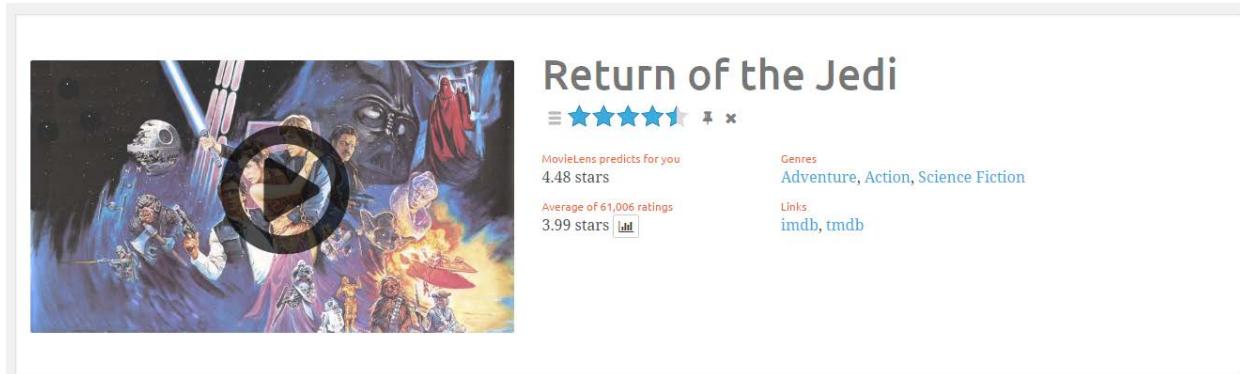
# Alternative Elicitation Techniques: Picture-Based



Source: [1]

[1] Julia Neidhardt, Leonhard Seyfang, Rainer Schuster, and Hannes Werthner. 2015. A picture-based approach to recommender systems. *Information Technology & Tourism* 15, 1 (2015), 49-69.

# Alternative Elicitation Techniques: Tag-Based



The image shows a screenshot of the MovieLens website for the movie "Return of the Jedi". At the top, there is a large thumbnail image of the movie poster featuring the main characters and the Death Star. Below the poster, there is a play button icon. To the right of the poster, the movie title "Return of the Jedi" is displayed in a large, bold font. Above the title is a rating of 4.48 stars out of 5. Below the rating, it says "MovieLens predicts for you" and "4.48 stars". Further down, it shows "Average of 61,006 ratings" and "3.99 stars". To the right of these statistics, there is a "Genres" section listing "Adventure, Action, Science Fiction" and a "Links" section with links to "imdb, tmdb".

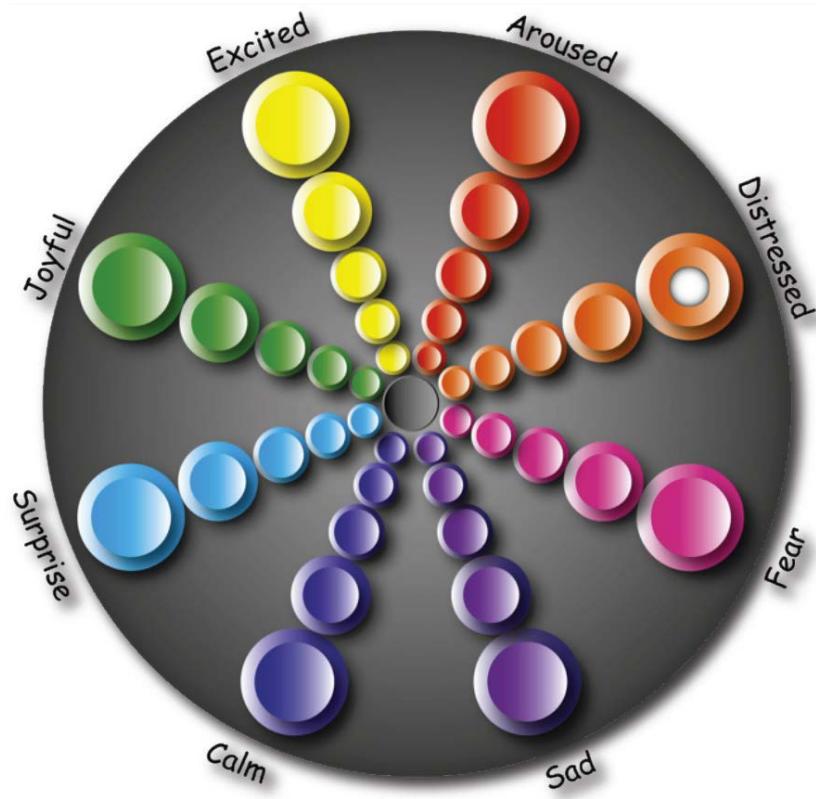
**Community Tags**

view: [top](#) [all](#)

<a href="#">x88 sci-fi</a> +	<a href="#">x66 Star Wars</a> +	<a href="#">x58 space</a> +	<a href="#">x46 Harrison Ford</a> +
<a href="#">x34 fantasy</a> +	<a href="#">x28 action</a> +	<a href="#">x20 aliens</a> +	<a href="#">x20 great soundtrack</a> +
<a href="#">x20 classic</a> +	Add to your tags: you like this about the movie		
<a href="#">x7 drama</a> +	Add to your tags: neutral	+ (Best Music)	<a href="#">x11 sequel</a> +
Add to your tags: you dislike this about the movie			
This tag does not apply, or is a bad tag			

Source: movielens.com

# Alternative Elicitation Techniques: Personality Quizzes



Source: [1]

[1] Yu Chen and Pearl Pu. 2012. CoFeel: An Interface for Providing Emotional Feedback in Mobile Group Recommender Systems. In *Joint Proceedings of the 1st International Workshop on Recommendation Technologies for Lifesyle Change (LIFESTYLE '12) and the 1st International Workshop on Interfaces for Recommender Systems (InterfaceRS '12)*. 48-55.

# Alternative Elicitation Techniques: Open Questions

- ▶ Interaction complexity
- ▶ User acceptance
  - ▶ Users have to “learn” something new
- ▶ Benefit compared to traditional systems
  - ▶ Good fit for some domains?
  - ▶ Fun?

# Interacting with Recommender Systems

Part II: Interactions during  
Result Presentation

# Exercise

## ► What could be changed?

The screenshot shows an Amazon product page for a Nikon D3300 camera. At the top, there's a 'Frequently Bought Together' section featuring a camera, a wireless adapter, and a memory card. Below it, another section titled 'Customers Who Bought This Item Also Bought' lists three related products: a wireless adapter, a camera shoulder bag, and a memory card. Each item has its price, a 'Prime' badge if applicable, and a star rating.

Item	Price	Rating
Nikon WU-1a Wireless Mobile Adapter for Nikon Digital SLRs	\$39.00	4.5 stars (1,729 reviews)
Lowepro Adventura 140 Camera Shoulder Bag for DSLR or Camcorder	\$26.99 Prime	4.5 stars (178 reviews)
Lexar Professional 633x 64GB SDXC UHS-I Card w/Image Rescue 5 Software - LSD64GCBX	\$22.50 Prime	4.5 stars (594 reviews)

Source: amazon.com

# Recommendation Result Presentation

- ▶ How present recommendations to the user?
- ▶ Common goals (purpose of the RS):
  - ▶ User satisfaction/retention
  - ▶ Increased purchase rate
- ▶ How to achieve this?
  - ▶ Reduce user effort/choice overload
  - ▶ Make exploration of item space fun/engaging

# Topics of This Session

- ▶ List design
- ▶ Visualization
- ▶ User feedback
- ▶ Proactivity
- ▶ Persuasion

# List Design

# List Design – Considerations

## Customers Who Bought This Item Also Bought

The screenshot shows a list of three items recommended for a Nikon AF-S FX NIKKOR 50mm f/1.8G Lens. Each item is displayed with its image, title, rating, price, and a 'Prime' badge if applicable. The items are:

- Nikon AF-S FX NIKKOR 50mm f/1.8G Lens with Auto Focus for Nikon DSLR Cameras**  
★★★★★ 1,505  
\$216.95 ✓Prime
- Lowepro Adventura 140 Camera Shoulder Bag for DSLR or Camcorder**  
★★★★★ 178  
\$26.99 ✓Prime
- Lexar Professional 633x 64GB SDXC UHS-I Card w/Image Rescue 5 Software...**  
★★★★★ 592  
\$22.50 ✓Prime

A callout box labeled "List label" points to the heading "Customers Who Bought This Item Also Bought". Another callout box labeled "Item description" points to the title of the third item. A callout box labeled "Community rating" points to the star rating and count for the third item. A callout box labeled "Highlighting" points to the "Best Seller" badge for the first item. A large bracket at the bottom is labeled "Number of options", pointing to the star rating and count for the third item.

List label

Item description

Community rating

Highlighting

Number of options

Source: amazon.com

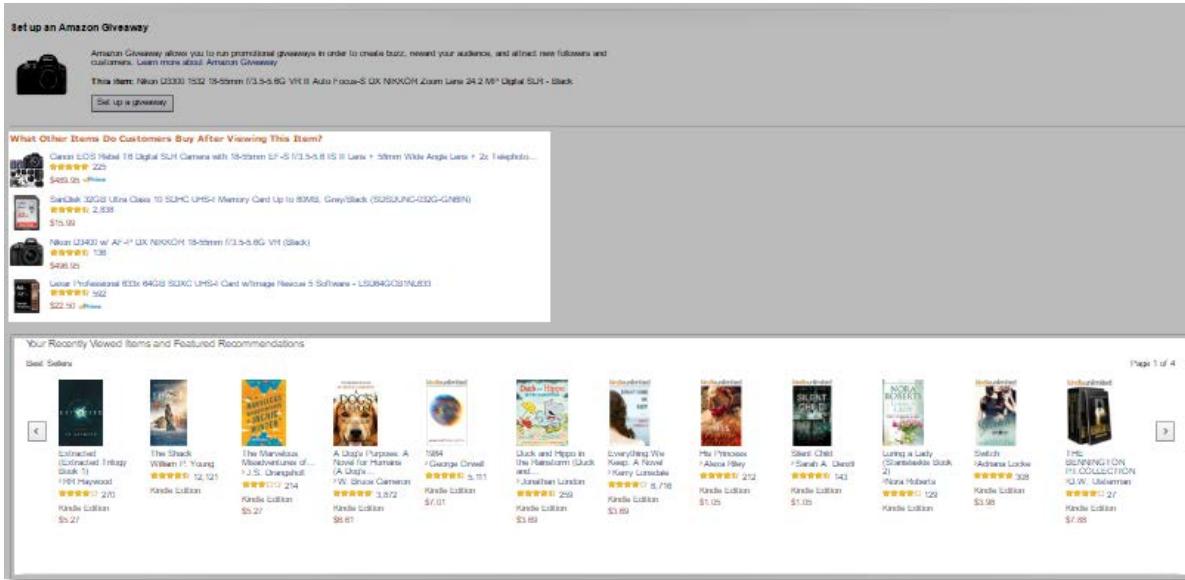
# List Design – Additional Considerations: Placement

The screenshot shows an Amazon product page for the Nikon D3300 18-55mm VR II lens. The page includes several recommendation sections:

- Frequently Bought Together:** Shows items like a Nikon WU-1a Wireless Mobile Adapter and a Lexar Professional 8GB SDXC UHS-I Card.
- Customers Who Bought This Item Also Bought:** Shows items such as a Nikon WU-1a Wireless Mobile Adapter, a Lexar Professional 8GB SDXC UHS-I Card, and a Nikon D3300 Camera.
- Other Sellers on Amazon:** Shows alternative sellers for the same product at different prices.
- Related Products:** Shows items like a Nikon AF-S DX NIKKOR 18-55mm f/3.5-5.6G VR II lens and a Nikon AF-S DX NIKKOR 18-55mm f/3.5-5.6G VR II lens.

Source: amazon.com

# List Design – Additional Considerations: Placement



Source: amazon.com

- ▶ How many lists?
- ▶ Where?
- ▶ Orientation?
- ▶ Visible on demand (hover, click, ...)?

# List Design – Psychological Principles

- ▶ Too few vs. too many options
  - ▶ Choice overload, reduced sales
- ▶ Finding a middle ground can also depend on:
  - ▶ User context
  - ▶ Item diversity
  - ▶ Comparability of items



Source: amazon.com



Source: amazon.com

# List Design – Psychological Principles

- ▶ Too few vs. too many options
  - ▶ Choice overload, reduced sales
- ▶ Finding a middle ground can also depend on:
  - ▶ User context
  - ▶ Item diversity
  - ▶ Comparability of items
  - ▶ List personalization
    - ▶ More or less effort/overload?

# Clustered Lists

- ▶ Group items
  - ▶ Semantically

The screenshot shows the Netflix homepage with three main categories highlighted by green boxes:

- Exciting TV Shows >** Includes thumbnails for "BLACKLIST", "DRAGONS: RACE TO THE EDGE", and "BITTEN".
- Comedies** Includes thumbnails for "THE BIG SHORT", "MIKE BIRBIGLIA", "Mike Birbiglia: Thank God For Jokes", and "DER NANNY".
- International TV Shows** Includes thumbnails for "THE CROWN", "GLITCH", and "AFRICA".

Source: netflix.com

- ▶ Technically

The screenshot shows an Amazon product page for a camera setup. It features a "Frequently Bought Together" section with the following items:

- A Nikon D3300 18-55mm f/3.5-5.6G VR II Auto Focus-S DX NIKKOR Zoom Lens.
- A Nikon WU-1a Wireless Mobile Adapter for Nikon Digital SLRs.
- A Lexar Professional 633x 64GB SDXC UHS-I Card w/Image Rescue 5 Software - LSD64GCB.

Total price: \$508.45

This item: Nikon D3300 1532 18-55mm f/3.5-5.6G VR II Auto Focus-S DX NIKKOR Zoom L  
 Nikon WU-1a Wireless Mobile Adapter for Nikon Digital SLRs \$39.00  
 Lexar Professional 633x 64GB SDXC UHS-I Card w/Image Rescue 5 Software - LSD64GCB

**Customers Who Bought This Item Also Bought**

- Nikon WU-1a Wireless Mobile Adapter for Nikon Digital SLRs
- Lowepro Adventura 140 Camera Shoulder Bag for DSLR or Camcorder
- Lexar Professional 633x 64GB SDXC UHS-I Card w/Image Rescue 5 Software...

Source: amazon.com

# Alternative List Designs

## ► Sortable/filterable lists

sorting by MovieLens recommendation

## all movies

view:

Filters:

- release date: >1980 ▾
- rated movies: hide ▾
- more ▾

sort by:

recommended ▾

Movie	Year	Rating	Length
No Country for Old Men	2007	R	122 min
Reservoir Dogs	1992	R	99 min
Indiana Jones and the Last Crusade	1989	PG-13	127 min

Source: movielens.org

# Alternative List Designs

- ▶ Sortable/filterable lists
- ▶ Alternatives to traditional “lists”
  - ▶ Grid
  - ▶ Pie/circle<sup>[1]</sup>



[1] Li Chen and Ho Keung Tsoi. 2011. Users' Decision Behavior in Recommender Interfaces: Impact of Layout Design. In *Joint Proceedings of the RecSys 2011 Workshop on Human Decision Making in Recommender Systems (Decisions@RecSys '11) and User-Centric Evaluation of Recommender Systems and Their Interfaces-2 (UCERSTI 2)* affiliated with the 5th Conference on Recommender Systems (RecSys '11). 21-26.

# List Design – Open Questions

- ▶ Large number of design options
  - ▶ One list vs. multiple (clustered) lists
  - ▶ List placement
  - ▶ Number of item, description detail
  - ▶ List layout
- ▶ Considerations:
  - ▶ Choice/information overload vs. satisfaction of the user's need for information/exploration
  - ▶ Consumer trust vs. persuasion to buy
  - ▶ Integration into corporate design
  - ▶ Domain specifics
  - ▶ ...

# Visualization

# Highlighting

- ▶ Instead of presenting a filtered list, highlight items



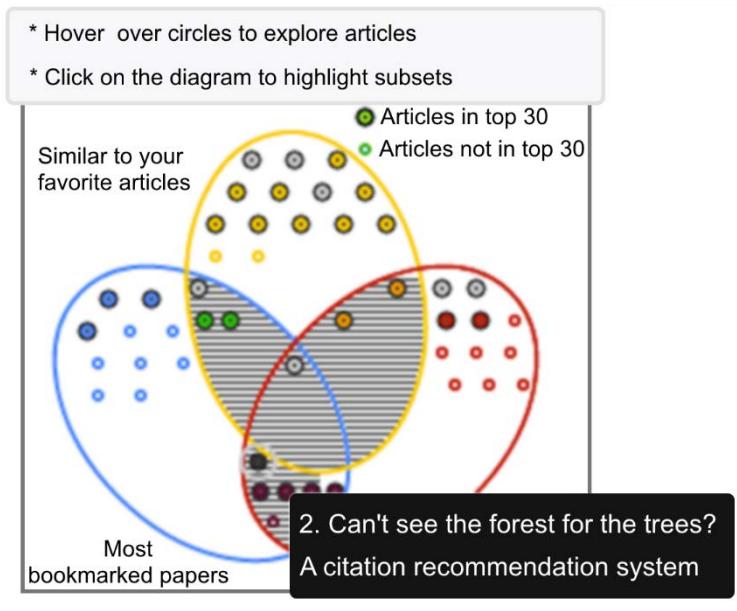
Source: [1]

- ▶ Familiar user experience with RS as added benefit
- ▶ No filtering -> higher user confidence?

[1] Wesley Waldner and Julita Vassileva. 2014. Emphasize, don't filter!: displaying recommendations in Twitter timelines. In *Proceedings of the 8th Conference on Recommender Systems (RecSys '14)*. 313-316.

# Diagrams and Graphs

- ▶ Use diagrams to communicate item relations



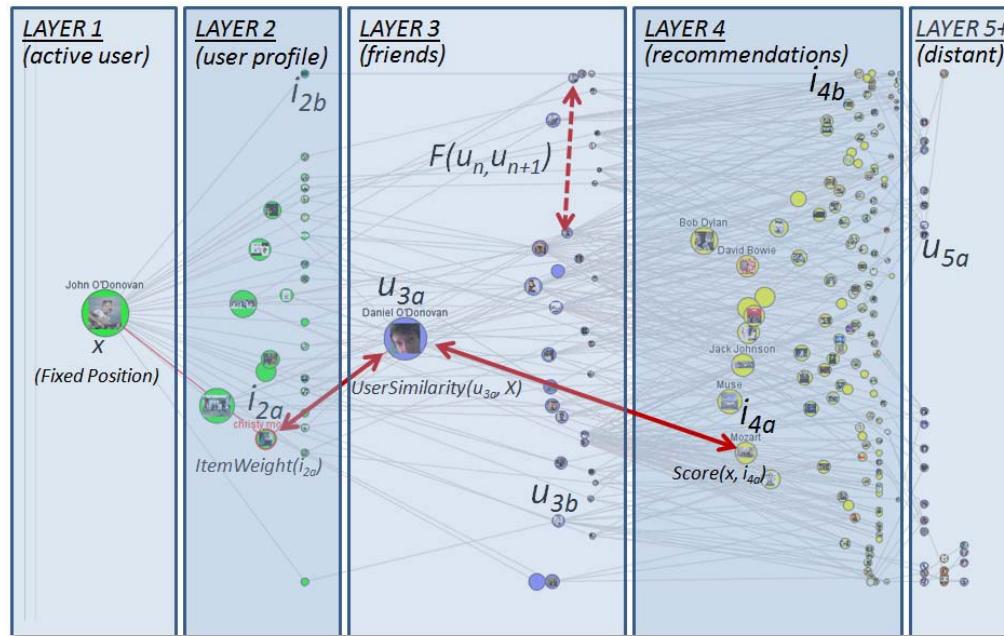
Source: [1]

- ▶ Easier for users or additional effort? Fun?

[1] Denis Parra, Peter Brusilovsky, and Christoph Trattner. 2014. See what you want to see: visual user-driven approach for hybrid recommendation. In *Proceedings of the 19th International Conference on Intelligent User Interfaces (IUI '14)*. 235-240.

# Diagrams and Graphs

- ▶ Use graphs to communicate item relations



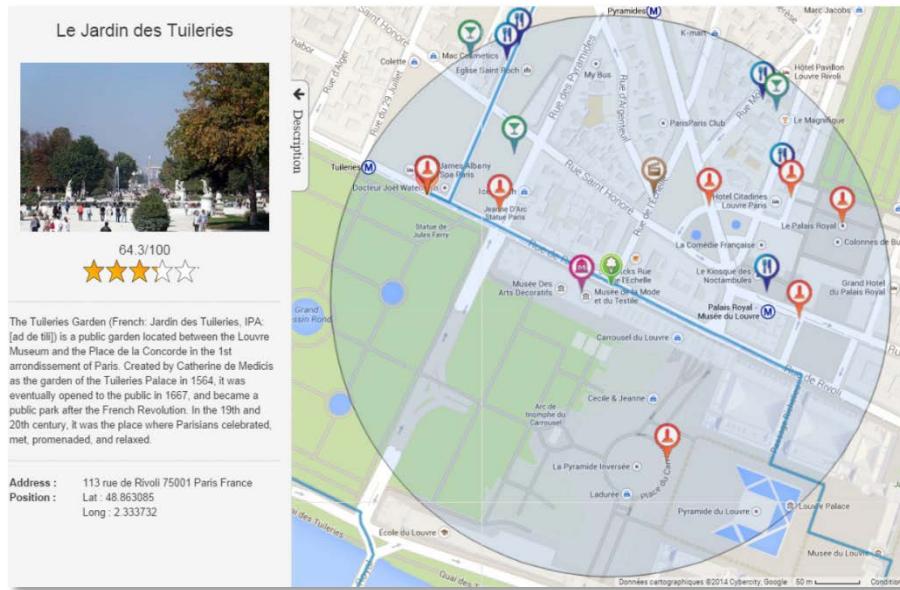
Source: [1]

- ▶ Easier for users or additional effort? Fun?

[1] Brynjar Gretarsson, John O'Donovan, Svetlin Bostandjiev, Christopher Hall, and Tobias Höllerer. 2010. Small-Worlds: Visualizing Social Recommendations. *Computer Graphics Forum* 29, 3 (2010), 833-842.

# Recommendations on Maps

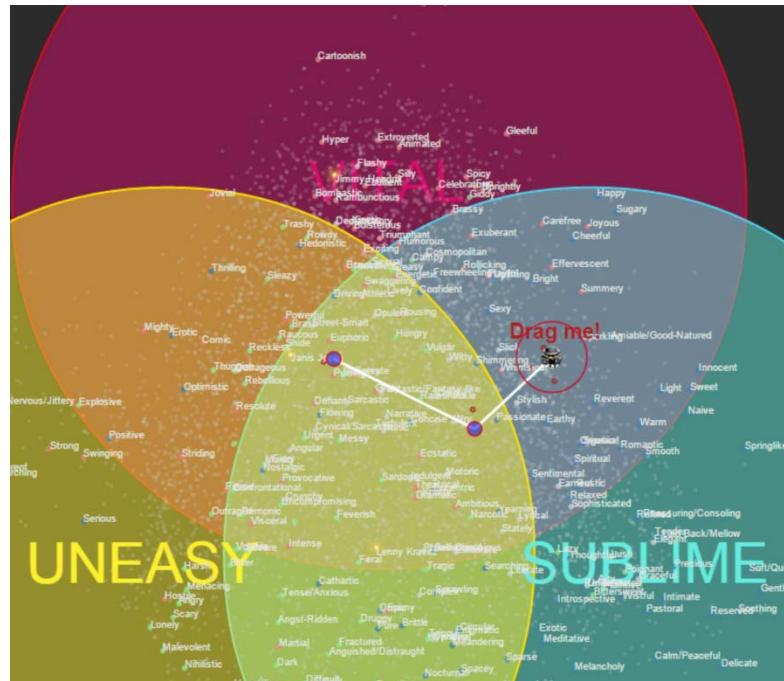
- ▶ Putting recommendations on maps is well-suited for some domains (e.g. POI recommendation)
- ▶ Great interaction possibilities (e.g. itinerary recommendations)



Source: [1]

# Recommendations in 2D space

- ▶ 2D plot can encompass “hidden feature space”
  - ▶ Possibility to include user in the plot  
-> interaction potential?

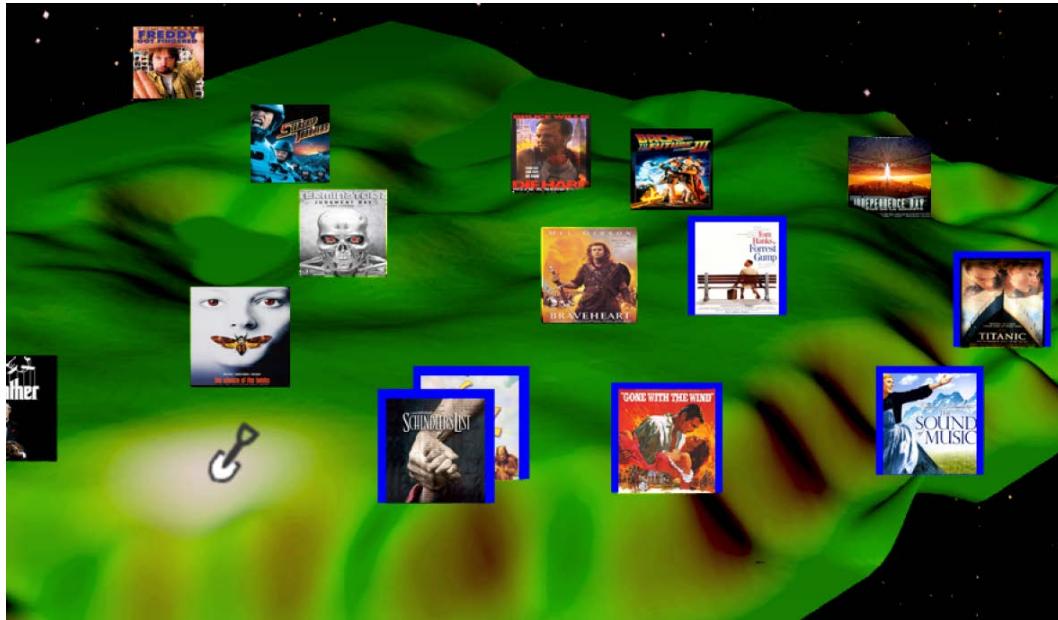


Source: [1]

[1] Ivana Andjelkovic, Denis Parra, and John O'Donovan. 2016. Moodplay: Interactive Mood-based Music Discovery and Recommendation. In *Proceedings of the 24th Conference on User Modeling, Adaptation, and Personalization (UMAP '16)*. 275-279.

# Recommendations in 3D space

- Additional 3<sup>rd</sup> dimension for extra information (e.g. user profile)



Source: [1]

[1] Johannes Kunkel, Benedikt Loepf, and Jürgen Ziegler. 2015. 3D-Visualisierung zur Eingabe von Präferenzen in Empfehlungssystemen. In *Proceedings of the 2015 Conference on Mensch und Computer 2015*. De Gruyter Oldenbourg, 123–132.

# Visualization – Open Questions

- ▶ Making exploration *fun* vs.  
making everyday use *convoluted*
- ▶ Extra information vs. extra effort
- ▶ Minuscule changes in practice -> huge impact on  
user experience -> experimentation dangerous?  
Never touch a running system?
- ▶ Exploration of emerging technologies:
  - ▶ Gamification
  - ▶ Virtual reality, Augmented reality
  - ▶ ...

# User Feedback

# User Feedback – General Idea

- ▶ So far:
  - ▶ Let users express their taste
  - ▶ Display (or visualize) recommendations
- ▶ What's missing?
  - ▶ Let users express their opinion about the recommendations
- ▶ Goals:
  - ▶ Correct faulty system assumption
  - ▶ Improve recommendations over time
  - ▶ Help users *feel more in control*

# User Feedback – Industry Approaches

- Well-hidden feature on amazon.com: feedback

The screenshot shows two sections of the Amazon.de website:

- Recommended for you:** A card for "Guardians of the Galaxy [Blu-ray]".
  - Image: Blu-ray cover for Guardians of the Galaxy.
  - Title: [Guardians of the Galaxy \[Blu-ray\]](#)
  - Format: Blu-ray ~ Chris Pratt (8 Jan 2015)
  - Status: In stock
  - Price: **EUR 9,99**
  - Other sellers: 73 used & new from EUR 8,75
  - Buttons: Add to Cart, Add to Wish List
  - Feedback: Rate this item (5 stars, checked), I own it, Not interested
- Because you purchased...**: A card for "Mad Max: Fury Road [Blu-ray] (Blu-ray)".
  - Image: Blu-ray cover for Mad Max: Fury Road.
  - Title: [Mad Max: Fury Road \[Blu-ray\]](#) (Blu-ray)
  - Format: DVD ~ Charlize Theron
  - Feedback: Rate this item (5 stars, checked), Don't use for recommendations

Source: amazon.de

- Also available on other platforms (e.g. music streaming “skip”), but often to a lesser extent

# User Feedback – Research Approaches

- ▶ Similar to Amazon's approach:

RECOMMENDED FOR YOU : Automatic Cross-Language Retrieval Using Latent Semantic Indexing

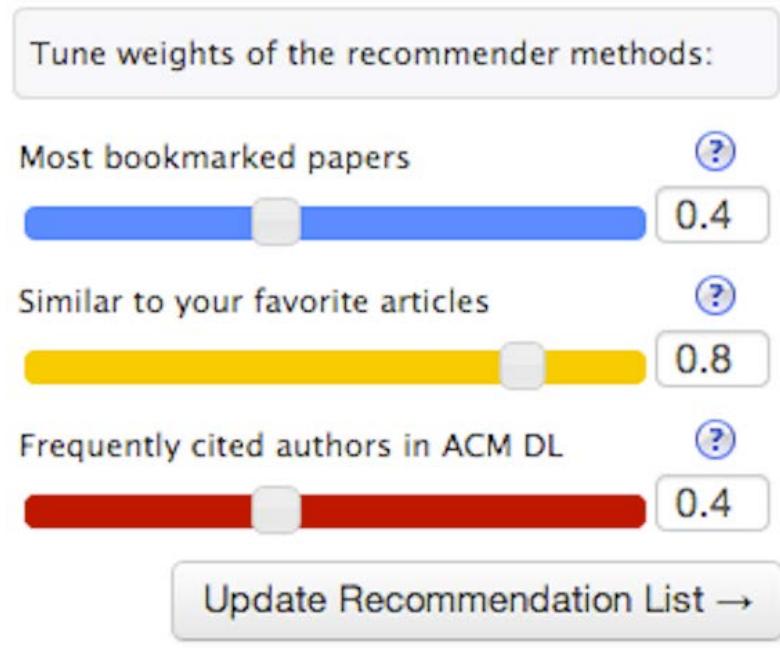
 <b>Journal Paper</b>  TITLE    Automatic Cross-Language Retrieval Using Latent Semantic Indexing  AUTHOR    ST Dumais, TA Letsche, ML Littman...  <a href="#">download document</a> <a href="#">download BibTeX</a>	<p>Topics of your interest included in this paper</p> <ul style="list-style-type: none"><li><input checked="" type="checkbox"/> automatic cross-language retrieval</li><li><input checked="" type="checkbox"/> constituent terms</li><li><input checked="" type="checkbox"/> direct term matching</li><li><input checked="" type="checkbox"/> document retrieval</li><li><input checked="" type="checkbox"/> dual-language document</li><li><input checked="" type="checkbox"/> dual-language semantic space</li><li><input checked="" type="checkbox"/> information retrieval</li><li><input checked="" type="checkbox"/> latent semantic indexing</li><li><input checked="" type="checkbox"/> singular value decomposition</li><li><input checked="" type="checkbox"/> vector method</li></ul> <p>Uncheck concepts to exclude them from future recommendations</p>	<p>Other topics included in this paper</p> <ul style="list-style-type: none"><li><input type="checkbox"/> training methods</li><li><input type="checkbox"/> multi-lingual semantic space</li><li><input type="checkbox"/> machine translation</li><li><input type="checkbox"/> important associative relationships</li></ul> <p>Check concepts to include them into future recommendations</p>
--	--	--

Source: [1]

- ▶ Additionally: positive feedback
  - ▶ Not only correction of the user profile  
-> augmentation

# User Feedback – Influencing the Strategy

- ▶ Let the user take full control



Source: [1]

- ▶ Can the user understand these options?

[1] Denis Parra, Peter Brusilovsky, and Christoph Trattner. 2014. See what you want to see: visual user-driven approach for hybrid recommendation. In *Proceedings of the 19th International Conference on Intelligent User Interfaces (IUI '14)*. 235-240.

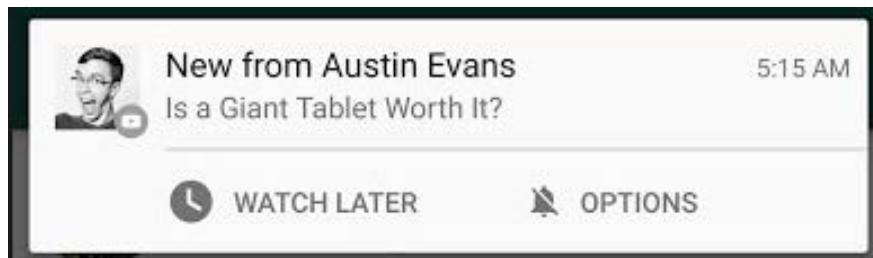
# User Feedback – Open questions

- ▶ Best feedback option?
  - ▶ Simple skip/dislike actions
  - ▶ Complex feedback options with explanations
  - ▶ In-depth profile inspection and manipulation
  - ▶ Manipulation of the recommendation strategy
- ▶ How to weight explicit item preferences (ratings) against feedback
- ▶ Do users feel more in control?
- ▶ Does it improve system accuracy?

# Proactive Recommendations

# Proactive Recommendations – General Idea

- ▶ So far: *user-initiated* interactions
- ▶ Now: *system-initiated* interactions
  - ▶ Recommend when the user is not even using the system
    - ▶ Email
    - ▶ App notification
    - ▶ ...



Source: YouTube app (Android)

# Proactive Recommendations – Open Questions

- ▶ How much is too much?
  - ▶ Notification frequency
  - ▶ Amount of content per notification
  - ▶ Explore-exploit
- ▶ Best time to notify?
  - ▶ Based on user context
  - ▶ Based on the user's attention level
- ▶ Does it accomplish provider goals?
- ▶ Can it have negative effects?

# Persuasive Recommender Systems

# Persuasive Recommender Systems

- ▶ Should the RS *persuade* the user to make the right choice or stay *neutral*?
- ▶ What is the right choice?
  - ▶ Best for the user -> RS as benevolent advisor
  - ▶ Best for the provider -> RS as exploitation device
  - ▶ Best/good for both -> win/win
- ▶ Ethical concerns?
- ▶ In RS research:
  - ▶ Persuasion with different psychological effects
    - ▶ Primacy, recency, anchoring, framing, decoy effect, etc.
    - ▶ Persuasion with explanations

# Interacting with Recommender Systems

Part III: Explanations

# Part III: Explanations

- ▶ A comprehensive overview of what has been done in the field of explanations in advice-giving systems
  - ▶ Expert systems
  - ▶ Decision-support systems
  - ▶ Knowledge-based systems
  - ▶ Recommender systems
- ▶ Insights
  - ▶ Explanation taxonomy
  - ▶ Open challenges

# Terminology

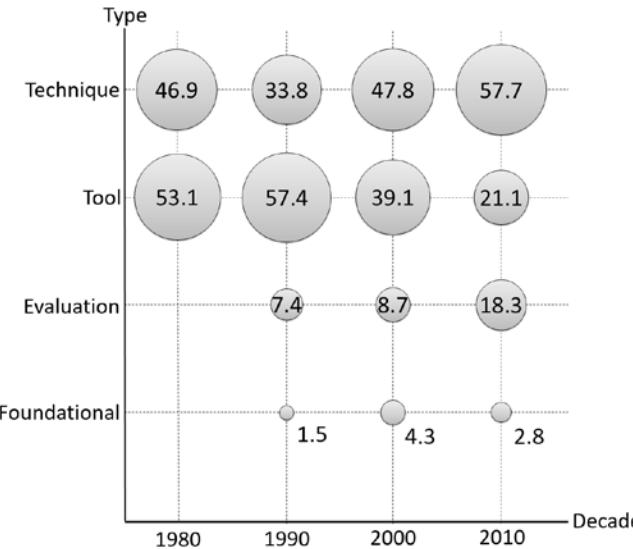
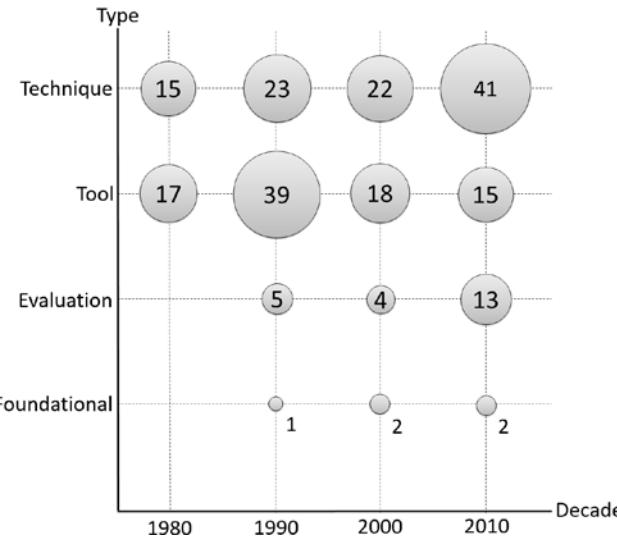
- ▶ Advice-giving systems
  - ▶ Expert Systems +
  - ▶ Decision-support Systems +
  - ▶ Knowledge-based Systems +
  - ▶ Recommender Systems
- ▶ Explanation
  - ▶ Information that is presented to the user
- ▶ Explanation generation approach
  - ▶ Technique or method that takes some data and transforms it into an explanation
- ▶ Decision inference method
  - ▶ Method that chooses an alternative from a set
    - ▶ E.g. decision technique or recommender algorithm
- ▶ Decision inference process
  - ▶ Execution of the decision inference method (an instance)

# Information Source

- ▶ Systematic review of the literature
- ▶ Query string: explanations + [system classes]
  - ▶ Synonyms: justification, argumentation
- ▶ 217 analysed primary studies
  - ▶ from 1209
- ▶ Digital databases
  - ▶ ACM, IEEE, Science Direct, Springer Link
- ▶ Categories
  - ▶ Techniques (101)
  - ▶ Tools (89)
  - ▶ Evaluation (22)
  - ▶ Foundational Study (5)

# Historical Developments

## The Rise-Fall-Rise of Explanations



- ▶ Publications increased in the recent past years\*
- ▶ Tools were largely important in the past
- ▶ Evaluations received much more attention recently
- ▶ Low number of foundational studies

\* Papers published before August 12, 2016

# Explanation Styles

Part III: Explanations

# Explanation Content

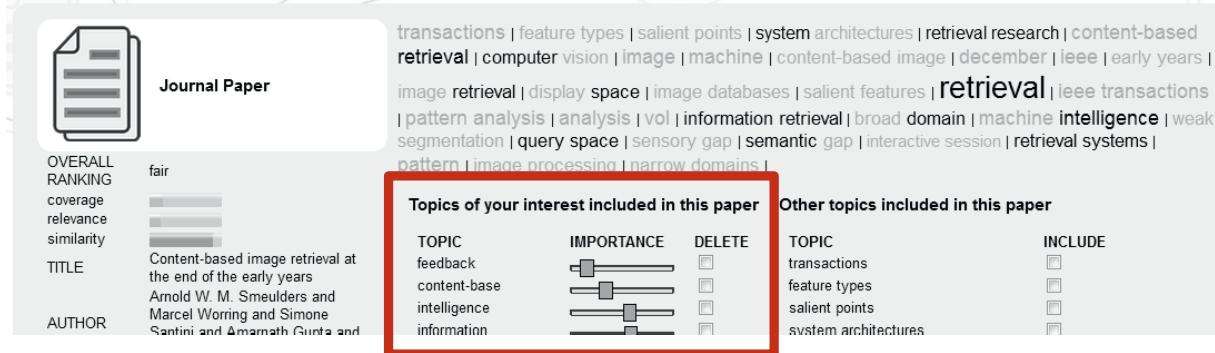
## Preferences and Inputs (1/2)

### ► Decisive Input Values

- If F1 is *very medium* AND F2 is *high*  
then likely class 1.

### ► Preference Match

Content-based image retrieval at the end of the early years



S. Mitra, S. K. Pal, Fuzzy multi-layer perceptron, inferencing and rule generation, IEEE Transactions on Neural Networks 6 (1) (1995) 51-63.

D. D. Nart, C. Tasso, A personalized concept-driven recommender system for scientific libraries, Procedia Computer Science 38 (2014) 84-91.

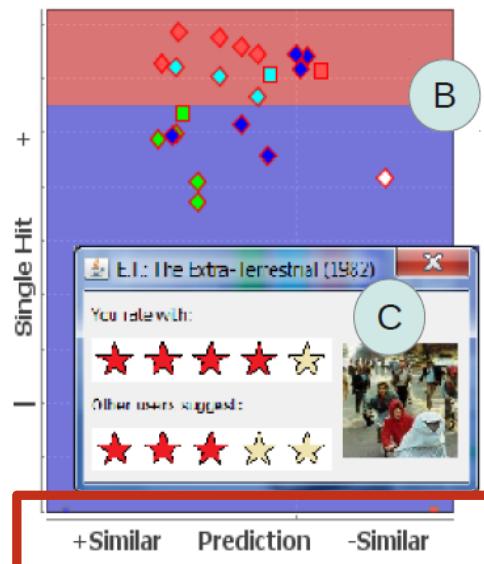
# Explanation Content

## Preferences and Inputs (2/2)

### ► Feature Importance Analysis

- Even though  $x$  is better than  $y$  on average,  $y$  is preferred to  $x$  since  $y$  is better than  $x$  on the criteria  $X$  that are **important** whereas  $y$  is worse than  $x$  on the criteria  $Y$  that are **not important**.

### ► Suitability Estimate



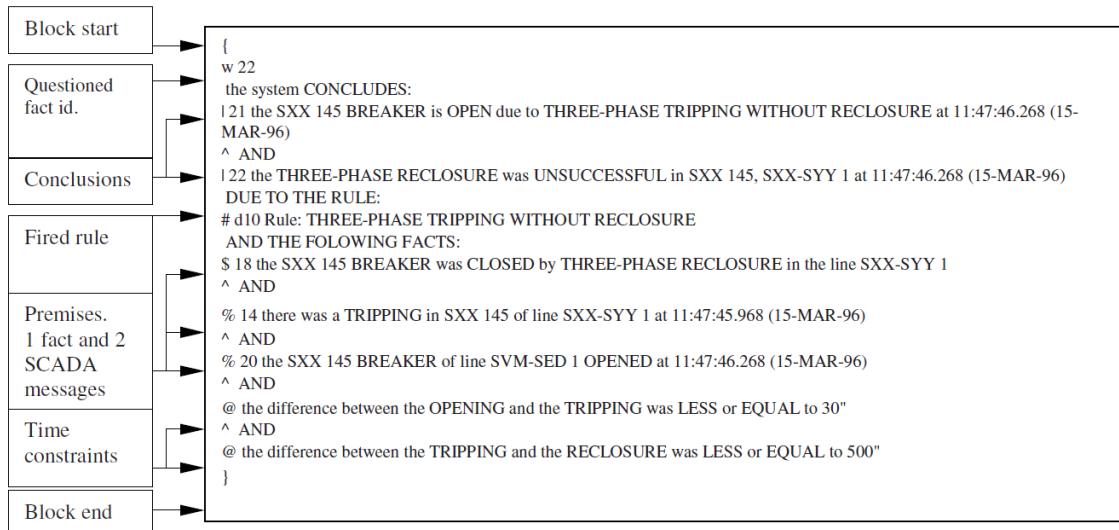
C. Labreuche, A general framework for explaining the results of a multi-attribute preference model, Artificial Intelligence 175 (7) (2011) 1410-1448.

Cleger-Tamayo, J. M. Fernandez-Luna, J. F. Huete, Explaining neighborhood-based recommendations, SIGIR '12, 2012, pp. 1063-1064

# Explanation Content

## Decision Inference Process (1/2)

### Inference Trace



### Inference and Domain Knowledge

#### *What is the goal of the action proposed?*

It was suggested to switch off the oxygen nozzle in order to reach the following goal(s): keep carbon percentage unchanged.

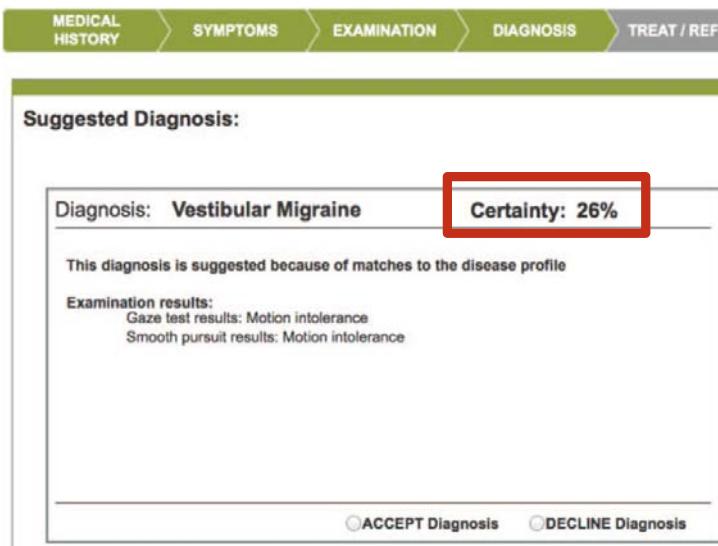
N. Malheiro, Z. A. Vale, C. Ramos, J. Santos, A. Marques, Enabling Client-Server Explanation Facilities in a Real-Time Expert System, Springer Berlin Heidelberg, 1999, pp. 333-342.

G. Guida, P. Mussio, M. Zanella, User interaction in decision support systems: the role of justification, in: 1997 IEEE International Conference on Systems, Man, and Cybernetics. Computational Cybernetics and Simulation, Vol. 4, 1997, pp. 3215-3220.

# Explanation Content

## Decision Inference Process (2/2)

### ► Inference Method Side-outcomes



### ► Self-reflective Statistics

User: Why did you suggest to view the temple of Hephestos?

Robot: Trust me, I have been correct in most cases (70%) in the past.

A. Bussone, S. Stumpf, D. O'Sullivan, The role of explanations on trust and reliance in clinical decision support systems, ICHI 2015, 2015, pp. 160-169.

D. Vogiatzis, V. Karkaletsis, A cognitive framework for robot guides in art collections, Universal Access in the Information Society 10 (2) (2011) 179-193.

# Explanation Content

## Background and Complementary Information (1/4)

### ► Knowledge about Similar Alternatives

#### Explanation

The DVD **Ocean's Twelve** is recommended to you, because

1. You clicked on DVD **Ocean's Eleven** ([hide](#))

That DVD has got the following similarities to DVD Ocean's Twelve:

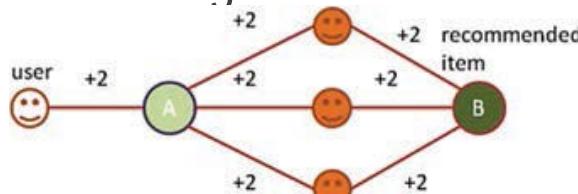
- o Film Genre: Comedy
- o Film Genre: Thriller
- o Person: Bernie Mac
- o Person: Brad Pitt
- o Person: George Clooney
- o Person: Matt Damon
- o Person: Steven Soderbergh
- o Type: Product
- o Type: DVD

Following argumentation(s) base(s) on endogenous factors, such as your click behavior:

- o **Ocean's Eleven** is performed by Person **Bernie Mac**, just like DVD **Ocean's Twelve**.  
Initiated by an exogenous factor: no. Induced energy: 0,143. Start age: 13. Length: 2.
- o **Ocean's Eleven** and DVD **Ocean's Twelve** are performed by the same Person (**Brad Pitt**).  
Initiated by an exogenous factor: no. Induced energy: 0,143. Start age: 13. Length: 2.

SPREADR inferred wrong? In order to get better recommendations you can [give feedback](#).

### ► Knowledge about Peers



Y.-C. Chen, Y.-S. Lin, Y.-C. Shen, S.-D. Lin, A modified random walk framework for handling negative ratings and generating explanations, ACM Trans. Intell. Syst. Technol. 4 (1) (2013) 12:1-12:21.

T. Hussein, S. Neuhaus, Explanation of spreading activation based recommendations, SEMAIS '10, 2010, pp.24-28.

# Explanation Content

## Background and Complementary Information (2/4)

### ► Knowledge about the Community

My car will run on... ✓  
( select those that apply )

Petrol  Diesel  LPG

I'm concerned about

Fuel Economy :	Least	1	2	3	4	5	6	7	8	9	10	Highly
Maintenance Cost :	0	1	2	3	4	5	6	7	8	9	10	✓
Resale Value :	0	1	2	3	4	5	6	7	8	9	10	✓
Safety :	0	1	2	3	4	5	6	7	8	9	10	✓
Comfort :	0	1	2	3	4	5	6	7	8	9	10	✓
Performance :	0	1	2	3	4	5	6	7	8	9	10	✓
Value For Money :	0	1	2	3	4	5	6	7	8	9	10	✓

2nd Best Recommendation

Audi A6 2.7 TDI  
Rs. 37,00,000  
Sedan Type, Luxury Car,  
5-Seater, 2698 CC, 6 Speed (AT\*),  
Mileage - 11.86 Km/ltr (Diesel)

FE: ★★★★★ MN: ★★★★★  
RV: ★★★★★ SF: ★★★★★  
CM: ★★★★★ PE: ★★★★★ VM: ★★★★★  
TR: ★★★★★ What is this?

[Check On-Road Price in your City](#) | [Get Quick Loan](#)

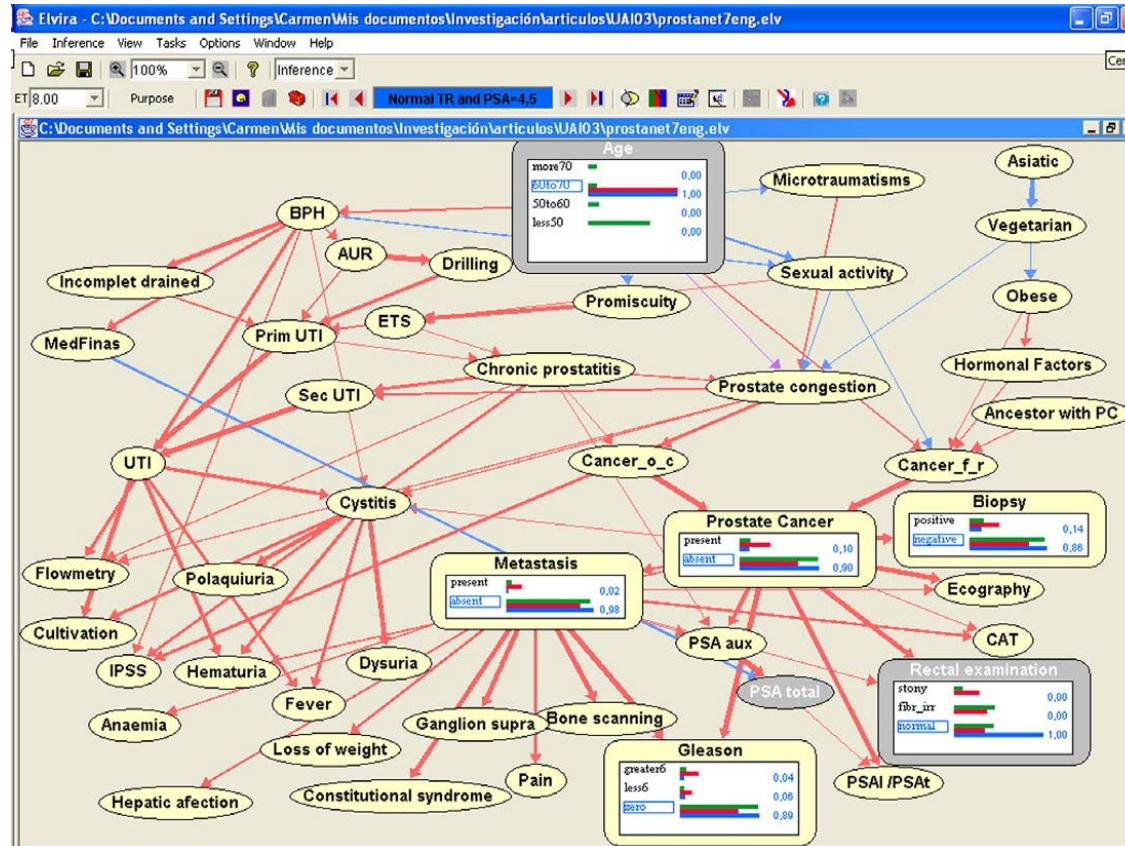
Audi A6 2.8 FSI  
Rs. 38,57,000  
Sedan Type, Luxury Car,  
5-Seater, 2773 CC, 6 Speed (AT\*),  
Mileage - 9.32 km/ltr (Petrol)

FE: ★★★★★ MN: ★★★★★  
RV: ★★★★★ SF: ★★★★★  
CM: ★★★★★ PE: ★★★★★ VM: ★★★★★  
TR: ★★★★★ What is this?

# Explanation Content

## Background and Complementary Information (3/4)

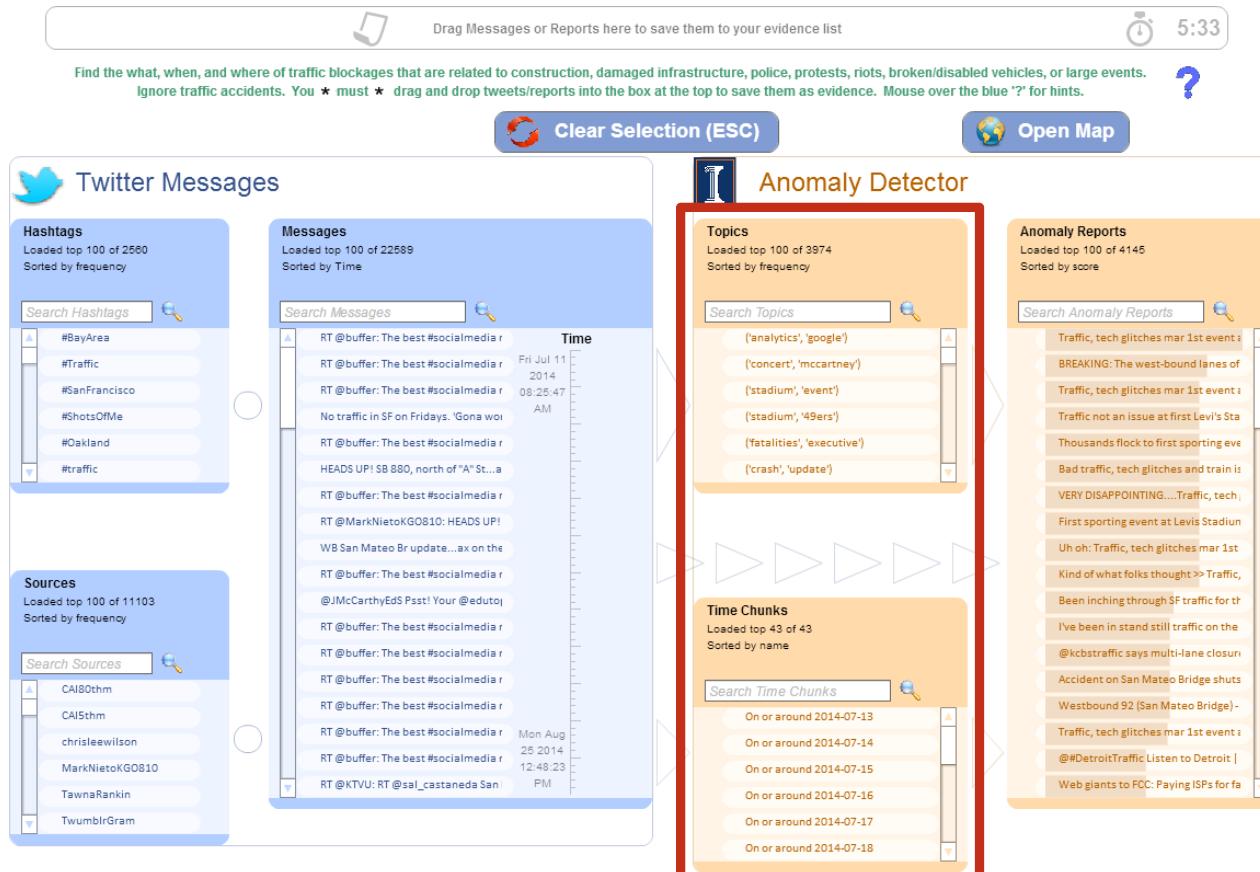
### ► Relationship between Knowledge Objects



# Explanation Content

## Background and Complementary Information (4/4)

### ► Background Data



# Explanation Content

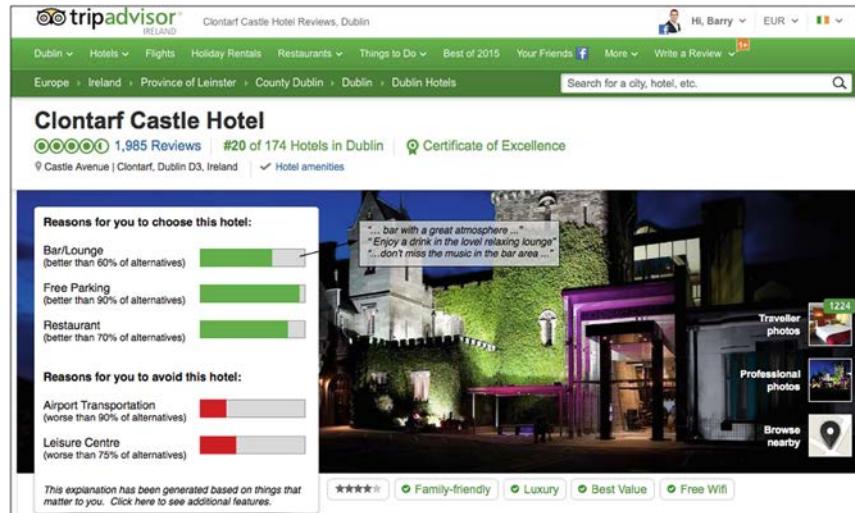
## Alternatives and their Features (1/2)

### ► Decisive Features

Your prediction is based on how MovieLens thinks you like these aspects of the film:

Your preference↓	
adventure	★★★★★
fun	★★★★★
action	★★★★★
sequel	★★★★★
egypt	★★★★★
comedy	★★★★★
brendan fraser	★★★★★

### ► Pros and Cons



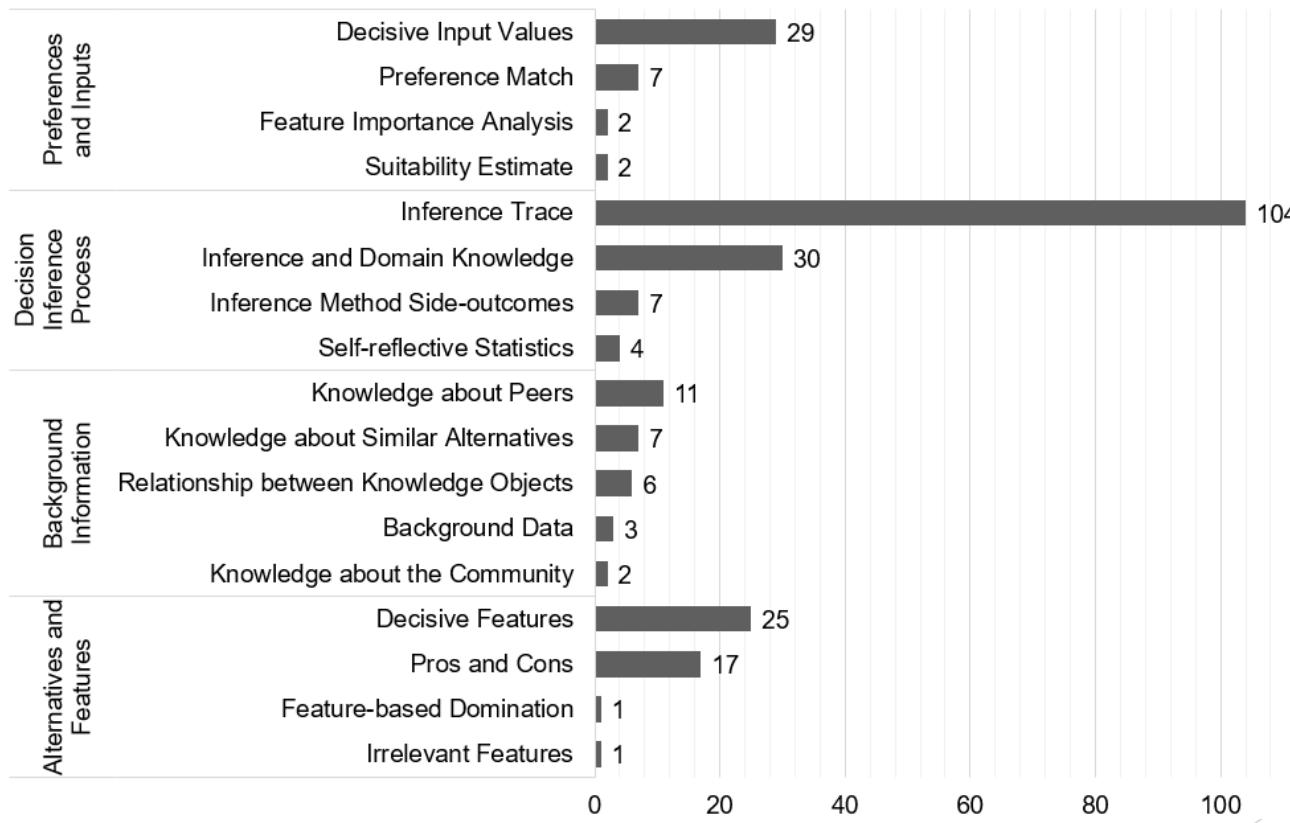
# Explanation Content

## Alternatives and their Features (2/2)

- ▶ Feature-based Domination
  - ▶ y is preferred to x since y is better than x on ALL criteria.
- ▶ Irrelevant Features
  - ▶ Case 574 differs from your query only in price and is the best case no matter what transport, duration, or accommodation you prefer

# Explanation Content

## Statistics



# Explanation Content

## Additional Observations

### ► Baselines and Multiple Alternatives

- Pairwise comparison or comparison with groups

The most popular product					
Manufacturer	Price	Processor speed	Battery life	Installed memory	Hard
○ -	\$2'095.00	1.67 GHz	4.5 hour(s)	512 MB	80 GB
We also recommend the following products because they are cheaper and lighter, but have lower processor speed					
○ -	\$1'499.00	1.5 GHz	5 hour(s)	512 MB	80 GB
○ -	\$1'739.99	1.5 GHz	4.5 hour(s)	512 MB	60 GB
○ -	\$1'625.00	1.5 GHz	5 hour(s)	512 MB	80 GB
○ -	\$1'426.99	1.5 GHz	5 hour(s)	512 MB	60 GB
○ -	\$1'929.00	1.2 GHz	4 hour(s)	512 MB	60 GB
○ -	\$1'595.00	1 GHz	5.5 hour(s)	512 MB	40 GB
they have higher processor speed and bigger hard drive capacity, but are heavier					
○ -	\$1'220.49	1.0 GHz	5 hour(s)	1 GB	100 G
○ -	\$2'149.00	2 GHz	4 hour(s)	1 GB	100 G
○ -	\$1'379.00	3.3 GHz	2 hour(s)	512 MB	100 G
○ -	\$2'235.00	1.8 GHz	2.5 hour(s)	1 GB	100 G
○ -	\$2'319.00	1.7 GHz	4.5 hour(s)	512 MB	100 G
○ -	\$2'075.00	1.8 GHz	1.67 hour(s)	512 MB	100 G

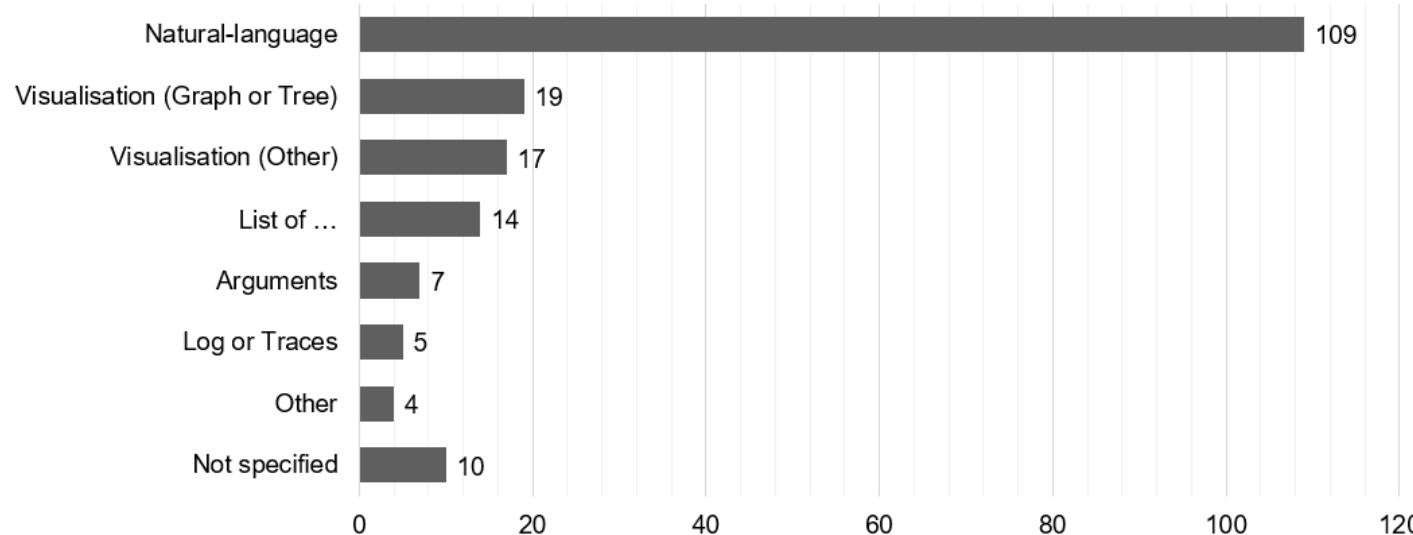
### ► Context-tailored Explanations

- Level of detail tailored to user expertise

### ► External Sources of Explanation Content

- Product reviews

# Explanation Presentation



- ▶ Other
  - ▶ Voice
  - ▶ Highlighting
  - ▶ Query results
  - ▶ OWL (Ontology Web Language)

# Explanation Generation Approaches

Part III: Explanations

# Explanation Generation

## Key Observations

- ▶ Few approaches provide sophisticated means of generating explanations
  - ▶ Use of knowledge data and inference process output
- ▶ Exceptions
  - ▶ Multi-criteria utility theory (MAUT)
    - ▶ Mathematical analysis of attribute weights and values
  - ▶ Artificial neural networks (ANN)
    - ▶ Rule extraction

# Explanation Generation

## Key Observations

- ▶ 18 (17.8%) approaches are **domain-specific**
  - ▶ E.g. domain-specific argument templates

---

### Postulate/Argument structure

---

Postulate 1: < recommend (Movie, User), good\_movie (Movie) ← avg\_rating (Movie)  
    > 3.8 >

Postulate 2: < recommend (Movie, User), likes\_by\_top genre (Movie, User) ←  
    top\_genre (User, Genre), genre (Movie, Genre) >

Postulate 3: < recommend (Movie, User), likes\_by\_top actor (Movie, User) ←  
    top\_actor (User, Actor), leads\_in (Movie, Actor) >

Postulate 4: < recommend (Movie, User), likes\_by\_top actor (Movie, User) ←  
    top\_actor (User, Actor), leads\_in (Movie, Actor), top\_genre (User, Genre), genre  
    (Movie, Genre) >

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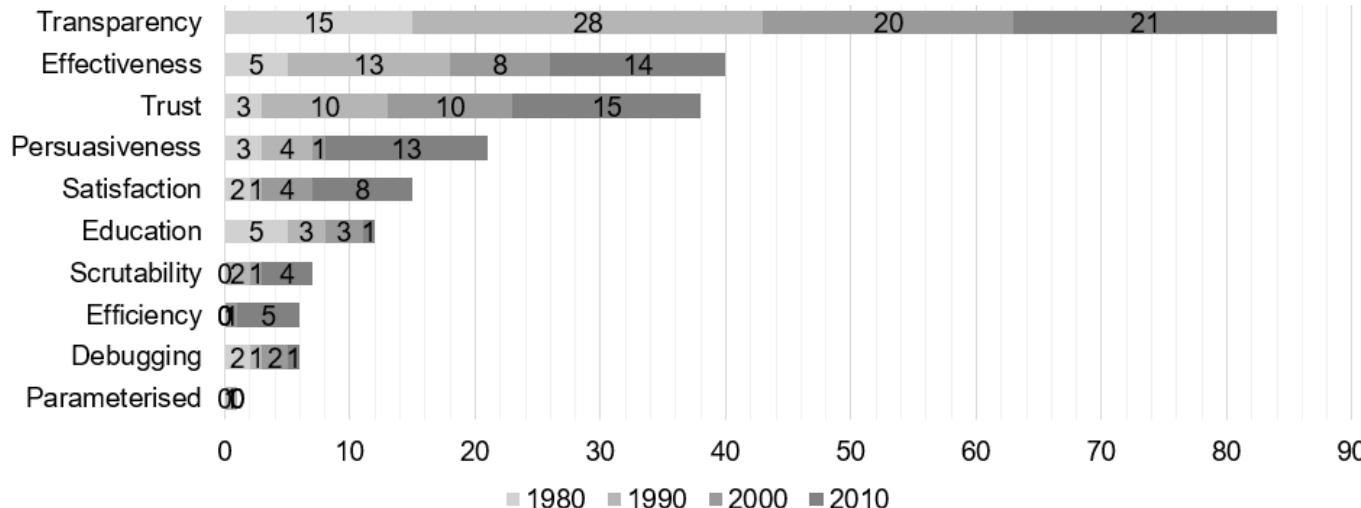
# Explanation Generation

## Key Drivers: (Intended) Purpose

Purpose	Description
Transparency	Explain how the system works
Effectiveness	Help users to make good decisions
Trust	Increase users' confidence in the system
Persuasiveness	Convince user to try or buy
Satisfaction	Increase the ease of usability or enjoyment
Education	Allow users to learn something from the system
Scrutability	Allow users to tell the system it is wrong
Efficiency	Help users make decisions faster
Debugging	Allows users to identify that there are defects in the systems

# Explanation Generation

## Key Drivers: (Intended) Purpose



- ▶ Transparency
  - ▶ Motivation: “[the] human user bears the ultimate responsibility for action” Moulin et al. [2002]
  - ▶ Means of achieving trust
- ▶ Persuasiveness, satisfaction, scrutability, and efficiency received more attention recently

# Explanation Generation

## Key Drivers: Decision Inference Method

Category	Subcategory	1980	1990	2000	2010	Total	%
Knowledge-based		33	50	28	31	142	68.3%
	<i>Rule-based</i>	28	33	11	7	79	55.63%
	<i>Logic-based</i>	2	3	3	8	16	11.27%
	<i>Multi-Criteria Decision Making</i>	0	1	3	5	9	6.34%
	<i>Constraint-based</i>	0	1	1	0	2	1.41%
	<i>Case-based Reasoning</i>	0	1	3	2	6	2.88%
	<i>Other</i>	3	11	7	9	30	21.13%
Machine Learning		2	13	12	24	51	24.5%
	<i>Feature-based</i>	2	13	6	11	32	62.75%
	<i>Collaborative-filtering</i>	0	0	5	5	10	19.61%
	<i>Hybrid</i>	0	0	1	8	9	17.65%
Mathematical Model		0	2	0	0	2	1.0%
Human-made Decision		0	1	0	1	2	1.0%
Algorithm-independent		0	3	3	5	11	5.3%

# Evaluation: Design & Conclusions

Part III: Explanations

# Evaluation Design

## Presence of an Evaluation

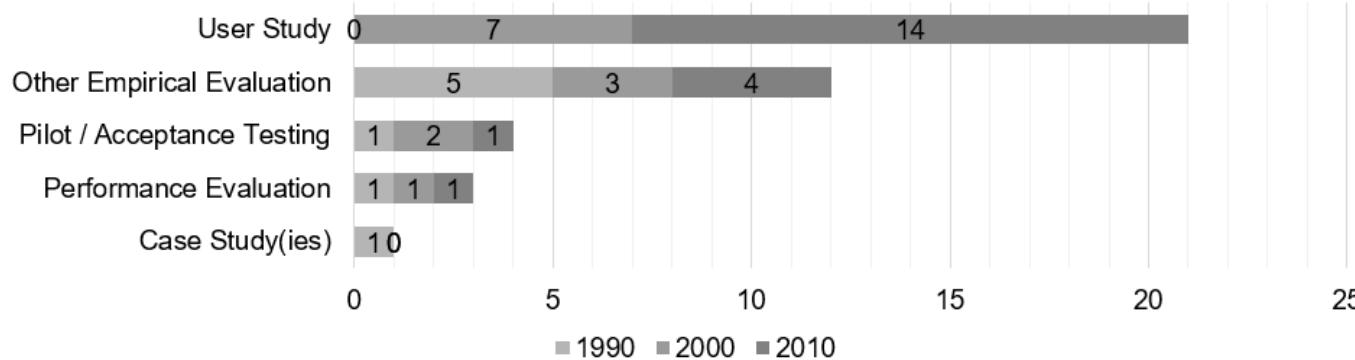
- ▶ How many of the explanation generation approaches were evaluated?

	1980	1990	2000	2010	Total
Technique	0%	22%	50%	46%	35%
Tool	0%	8%	6%	7%	6%
<b>Total</b>	<b>0%</b>	<b>13%</b>	<b>30%</b>	<b>36%</b>	<b>21%</b>

- ▶ Past
  - ▶ Lower methodological requirements
- ▶ Present
  - ▶ Still not the majority
  - ▶ Some approaches
    - ▶ Main contribution is an **algorithm** (explanation is an add-on)

# Evaluation Design

## Evaluation Types



- ▶ User study is the most frequent
  - ▶ All 22 evaluation studies involve user studies
- ▶ Other empirical evaluation
  - ▶ Different choices, e.g. explanation coverage
- ▶ Most explored domains
  - ▶ Media Recommendation, Health, and (e-)Commerce

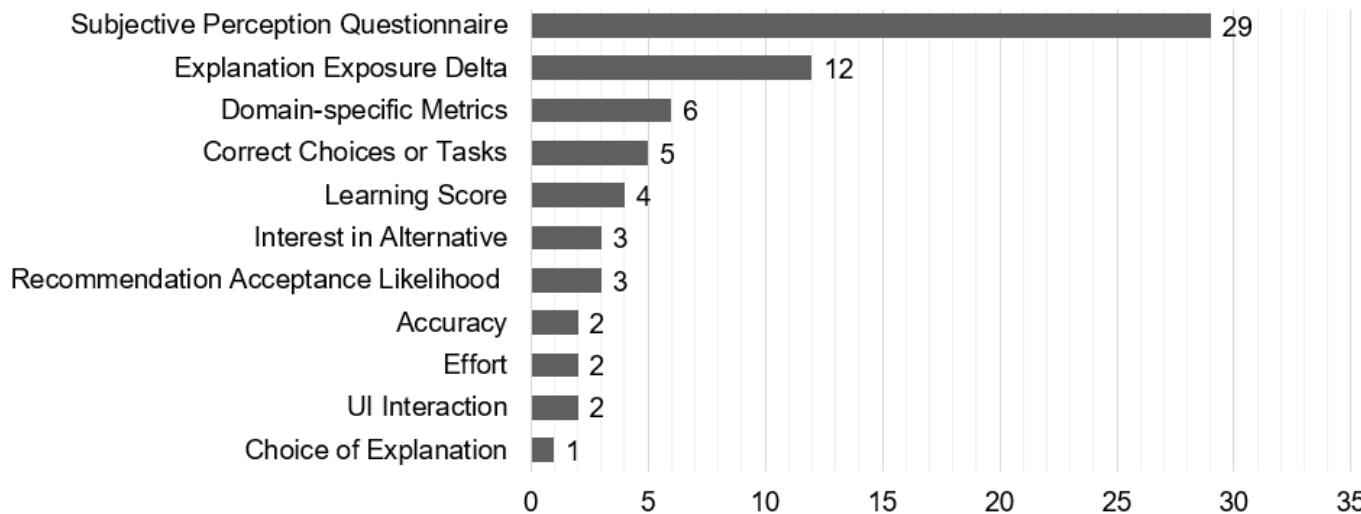
# Evaluation Design

## User Studies: Independent Variables

- ▶ Single treatment
- ▶ With explanations vs. no explanations
- ▶ Alternative explanations
  - ▶ Most frequent
  - ▶ From 2 to 9, exception 21
  - ▶ May include no explanations
- ▶ Alternative user interfaces/RS versions
  - ▶ From 2 to 9
- ▶ Other
  - ▶ confidence, direction, length, robot ability, ...

# Evaluation Design

## User Studies: Dependent Variables



# Evaluation Design

## User Studies: Dependent Variables

- ▶ Subjective perception questionnaire example

- ▶ How much do you think the explanation was helpful for you to make better decisions?  efficiency\*
- ▶ How good do you think the explanation was?  satisfaction

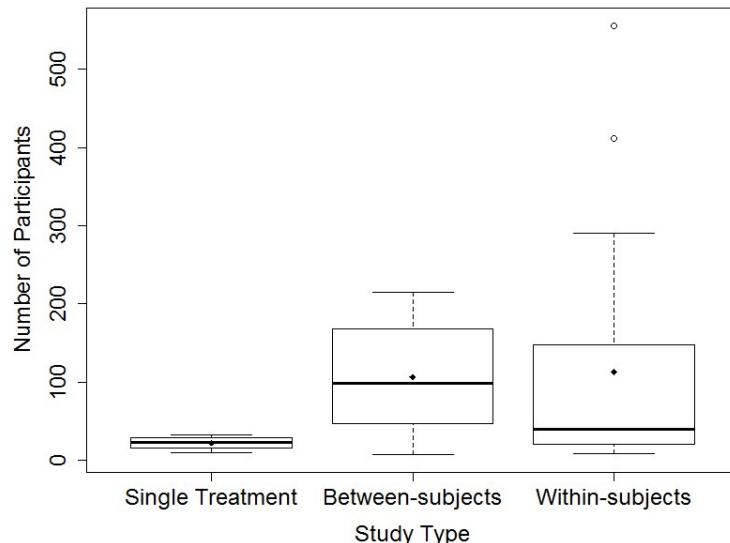


\*According to Tintarev and Masthof's definition, this should be effectiveness. However, the authors used the term efficiency in the paper: "W. Hanshi and F. Qiuje and L. Lizhen and S. Wei, A probabilistic rating prediction and explanation inference model for recommender systems, China Communications, 2016, pp. 79-94."

# Evaluation Design

## User Studies: Sample Size

- ▶ Largest study: within-subjects (556 participants)
- ▶ Highest mean: between-subjects
- ▶ Single treatment studies: low number of participants
- ▶ Number of factors do not influence sample size



# Evaluation Results

## User Studies

Purpose	Positive	Neutral	Negative
Effectiveness	+++++	~~~	
Transparency	+++++	~	
Persuasiveness	++		-
Satisfaction	+++		
Trust	+++	~~	
Usefulness	+++		
Ease of Use	+	~~	
Efficiency	+		--
Education	+	~~	

# Evaluation Results

## User Studies

- ▶ Effectiveness
  - ▶ Divergent results
  - ▶ Specific explanation styles are more effective
  - ▶ Presence of confounding variables?
- ▶ Persuasiveness
  - ▶ Social information (e.g. ratings) is more persuasive
- ▶ Transparency and most of user-centric purposes
  - ▶ Generally positive results
- ▶ Ease of Use
  - ▶ Extra information decreases usability
  - ▶ Organisation of recommendations has a positive effect
- ▶ Efficiency
  - ▶ Follows ease of use

# Evaluation Results

## User Studies

- ▶ Personalisation
  - ▶ +: Satisfaction and Transparency
  - ▶ -: Effectiveness and efficiency
- ▶ Expertise Levels
  - ▶ Experts and novices have different preferences over explanations
- ▶ Explanation Direction
  - ▶ Negative explanations are more influential than positive explanation
- ▶ Explanation Confidence and Length
  - ▶ Strongly confident and long explanations are more persuasive

# Evaluation Results

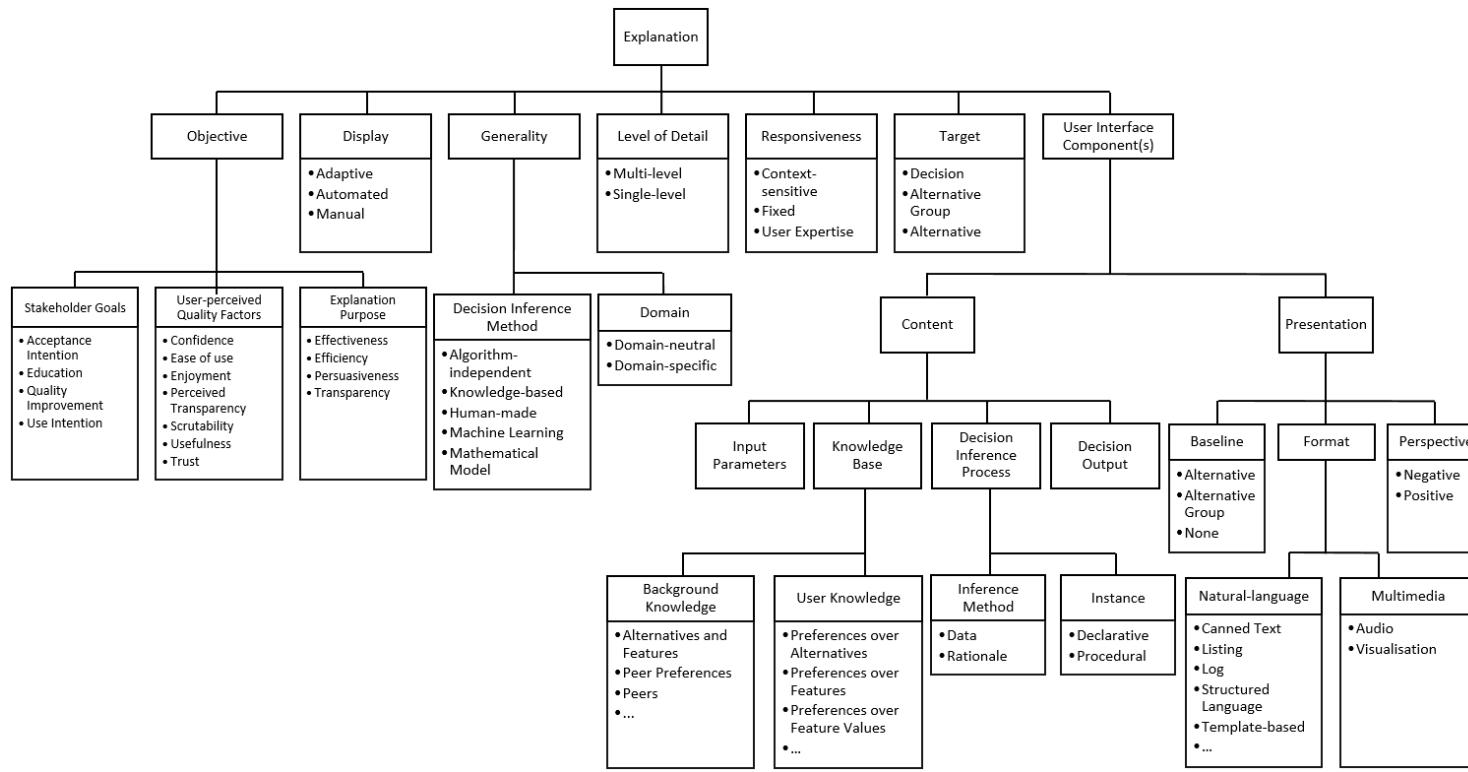
## Foundational Studies

- ▶ Tintarev and Masthoff (*RecSys 2007*)
  - ▶ Explanations must be customised to the user and the context, by selecting features from the suggested alternative accordingly
- ▶ Nunes et al. (*UMAP 2012*)
  - ▶ Guidelines and patterns
  - ▶ Explanations should be concise and focus on the most relevant criteria
- ▶ General aspects related to explanations
  - ▶ Mental models: improved decisions if users understand ES's reasoning process and provided information
    - ▶ *Rook and Donnell, IEEE Trans. on Systems, Man, and Cybernetics, 1993*
  - ▶ Cognitive fit: increased KBS acceptance if the KBS explanations match users' internal explanations
    - ▶ *Giboney et al., DSS, 2015*
  - ▶ Explanations have greater usefulness when decision support systems are used as a cooperative problem solving tool
    - ▶ *Gregor, IJHCS, 2001*

# A Comprehensive Explanation Taxonomy

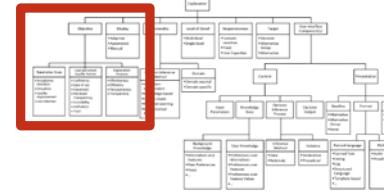
Part III: Explanations

# Explanation Taxonomy



# Explanation Taxonomy

## Objective



### Stakeholder Goals

Acceptance Intention

Education

Use Intention

Quality Improvement



### User-perceived Quality Factors

Confidence

Ease of Use

Enjoyment

Perceived Transparency

Scrutability

Usefulness

Trust



### Explanation Purpose

Effectiveness

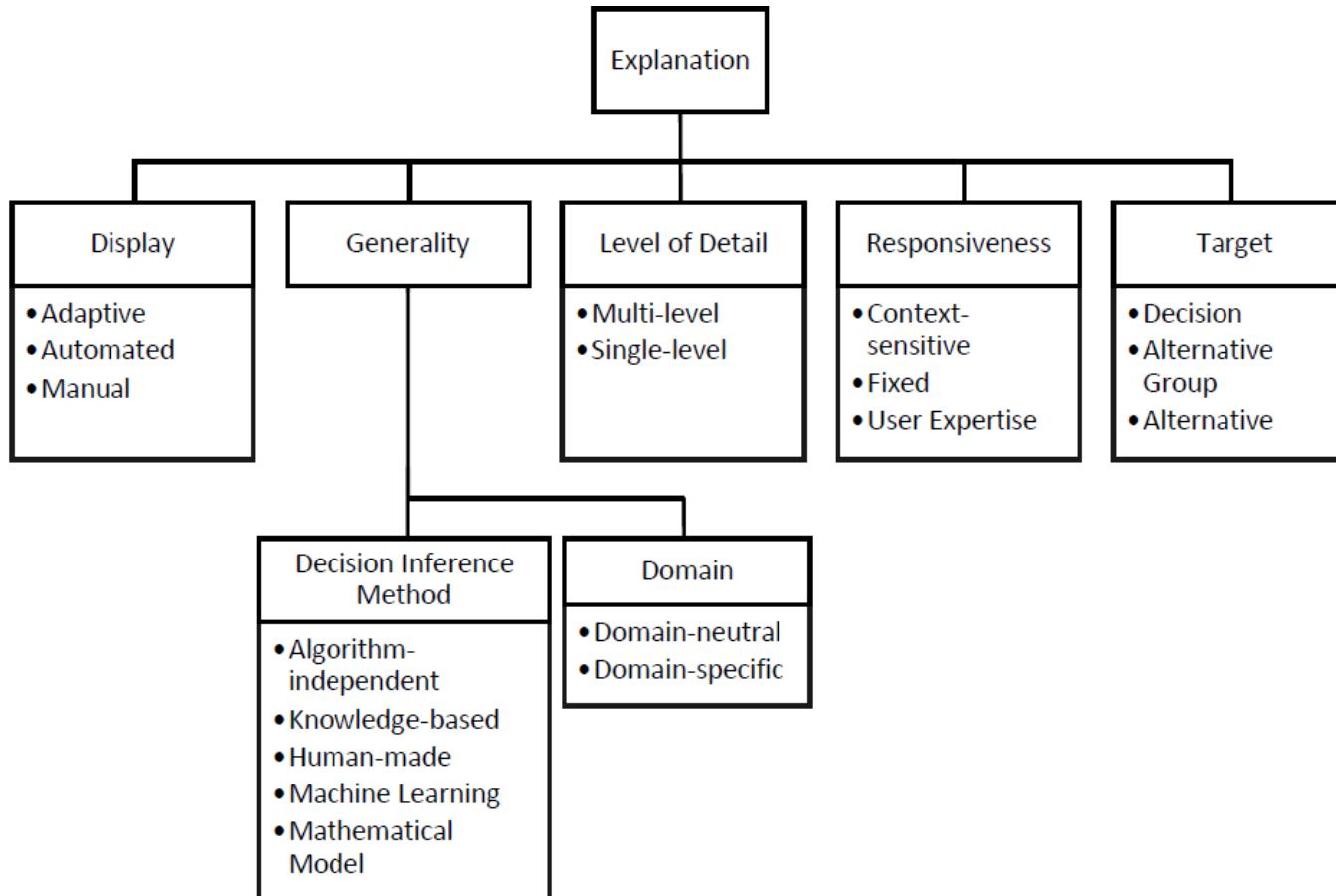
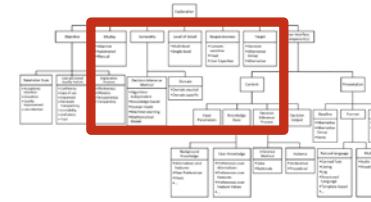
Efficiency

Persuasiveness

Transparency

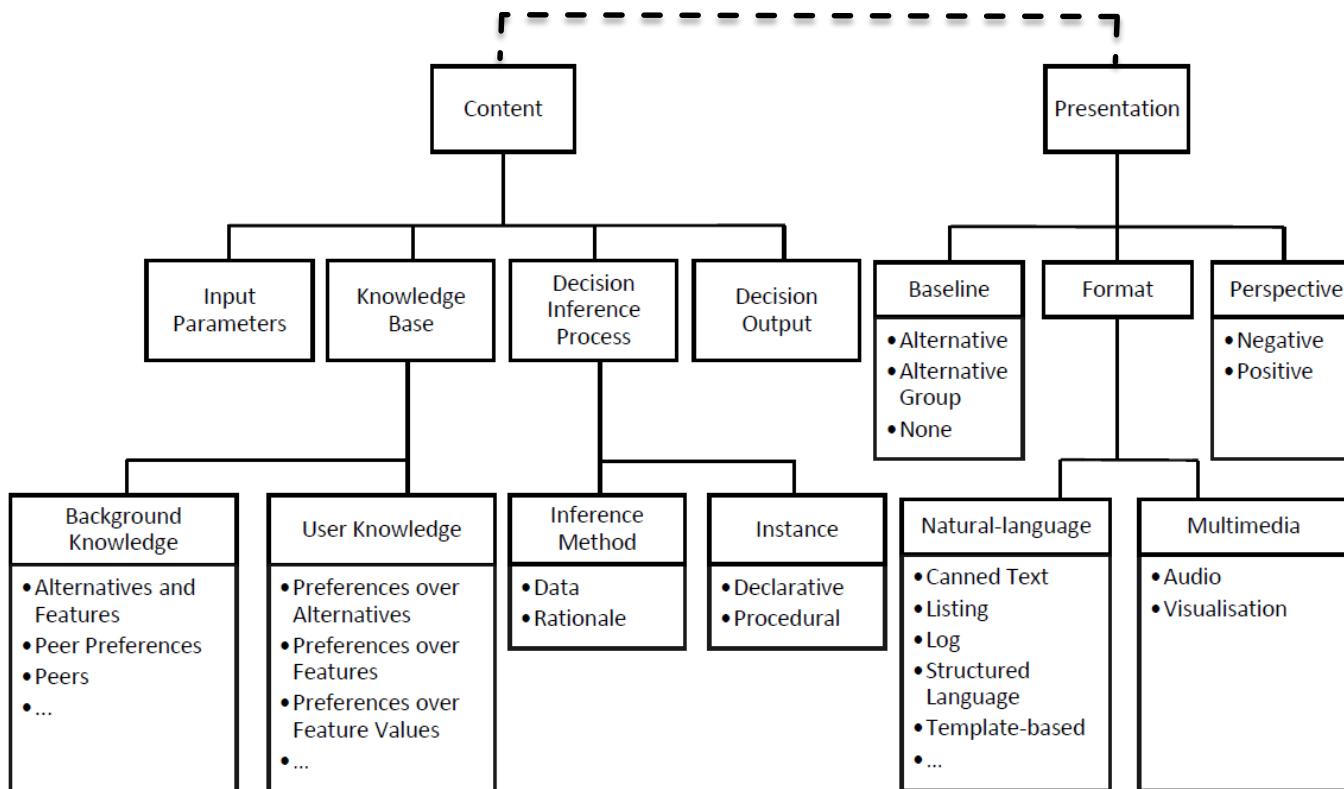
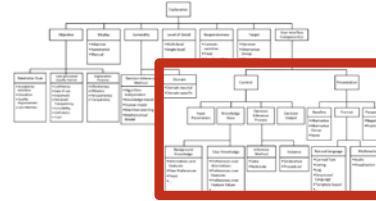
# Explanation Taxonomy

## General Facets



# Explanation Taxonomy

## User Interface Component(s)



# Open Challenges

- ▶ Understanding the relationship among stakeholder goals, user-perceived quality factors, and explanation purposes
- ▶ Selecting the right explanation content
  - ▶ Inference traces: a rule in the past
  - ▶ Today: why an alternative is adequate helpful for users
- ▶ Investigating fine-grained details of presentation aspects
  - ▶ Length, vocabulary, format
  - ▶ Real transparency vs. perceived transparency
- ▶ Towards more responsive explanations
  - ▶ Only 16 (8%) approaches consider this
- ▶ The need for adequate objective evaluation protocols and metrics
  - ▶ Objective measurements

# Interacting with Recommender Systems

Conclusions and Discussion

# Summary

- ▶ A variety of advanced user interaction approaches have been proposed over the years
  - ▶ Nonetheless, a niche topic in academia
  - ▶ Community focuses on algorithms, which is only one component of a recommender system
  - ▶ UI design however a relevant success factor in practice
  - ▶ “Academic” UI designs often comparably complex

# Main Challenges

- ▶ Many open questions raised throughout the tutorial
  - ▶ How to acquire user preferences
  - ▶ How to present results and collect feedback
  - ▶ How to explain (with a certain purpose in mind)
- ▶ Methodological aspects
  - ▶ User studies of various designs as main instrument
  - ▶ Nearly no standard protocols or evaluation frameworks exist
- ▶ Interdisciplinary approach required
  - ▶ Within computer science and outside

# Future directions

- ▶ Personalized interaction
  - ▶ Different UIs for different users
  - ▶ User feedback
- ▶ Natural language interfaces
  - ▶ Voice control, chat bots
- ▶ Designing interaction patterns with a purpose in (e.g., persuasion)
- ▶ Augmented reality/virtual reality
  - ▶ Interact in the real/virtualized world
- ▶ More context-aware and adaptive UIs
  - ▶ Mobile devices, new sensors

# Thank you

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- ▶ Upcoming paper:  
Jugovac, M., Jannach, D.: Interacting with Recommenders - Overview and Research Directions, ACM Transactions on Intelligent Interactive Systems (TiIS).