Explaining recommendations

Explanations in recommender systems

Motivating example

- ▸ "The digital camera *Profishot* is a must-buy for you because …."
- ▸ Why should recommender systems deal with explanations at all?
- ▸ In e-commerce settings, the answer is related to the two parties providing and receiving recommendations:
    - ▸ A selling agent may be interested in promoting particular products
    - ▸ A buying agent is concerned about making the right buying decision

Explanations at Amazon.de

Neuerscheinung
Die andere Heimat …
Jan Schneider
★★★★★ (6)
EUR 14,99
Warum empfohlen?

Why recommended ?

amazon.de

Unsere Empfehlungen für Sie

Die andere Heimat [Blu-ray]
Blu-ray ~ Jan Schneider *(10. Juli 2014)*
Vorbestellbar
Preis: EUR 14,99

Diesen Artikel bewerten
☒ ☆☆☆☆☆
▢ Gehört mir
▢ Kein Interesse

[Jetzt vorbestellen] [Auf meinen Wunschzettel]

Denn Sie haben gekauft:

Panasonic ER-1611 Profi-Haarschneidemaschine

☒ ☆☆☆☆☆
▢ Nicht für Empfehlungen berücksichtigen

Because you bought …

Do not use for recommendations

3

What is an Explanation?

‣ "A piece of information exchanged in a communication process"
‣ Brewer et al. (1998) distinguishes between
  ‣ **functional,**
    ‣ "The car type Jumbo-Family-Van of brand Rising-Sun would be well suited to your family because you have four children and the car has seven seats"
  ‣ **causal,**
    ‣ "The light bulb shines because you turned it on"
  ‣ **intentional,**
    ‣ "I washed the dishes because my brother did it last time"
    ‣ "You have to do your homework because your dad said so"
  ‣ **and scientific explanations**
    ‣ Express relations between the concepts formulated in various scientific fields and are typically based on refutable theories

Explanations in recommender systems

Additional information to explain the system's output following some objectives
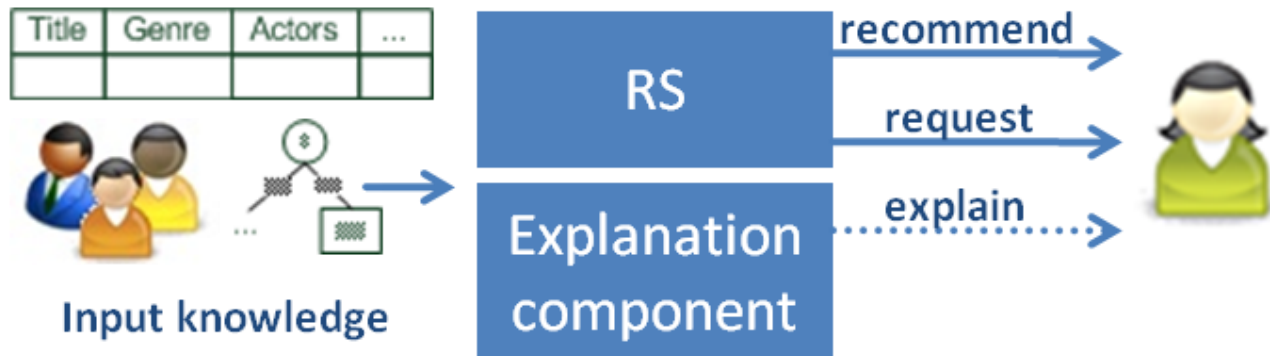
Goals when providing explanations (1)

‣ Transparency
  ‣ Provide information so the user can comprehend the reasoning used to generate a specific recommendation
  ‣ Provide information as to why one item was preferred over another

‣ Validity
  ‣ Allow a user to check the validity of a recommendation
  ‣ Not necessarily related to transparency
    ‣ E.g., a neural network (NN) decides that product matches to requirements
    ‣ Transparent disclosure of NN's computations will not help, but a comparison of required and offered product features allows customer to judge the recommendation's quality.

Goals when providing explanations (2)

▸ **Trustworthiness**
  - ▸ Trust building can be viewed as a mechanism for reducing the complexity of human decision making in uncertain situations
  - ▸ Reduce the uncertainty about the quality of a recommendation

▸ **Persuasiveness**
  - ▸ Persuasive explanations for recommendations aim to change the user's buying behavior
  - ▸ E.g., a recommender may intentionally dwell on a product's positive aspects and keep quiet about various negative aspects

▸ **Effectiveness**
  - ▸ The support a user receives for making high-quality decisions
  - ▸ Help the customer discover his or her preferences
  - ▸ Help users make better decisions

Goals when providing explanations (2)

Goals when providing explanations (3)

▸ Efficiency
  ▸ Reduce the decision-making effort
  ▸ Reduce the time needed for decision making
  ▸ Another measure might also be the perceived cognitive effort

▸ Satisfaction
  ▸ Improve the overall satisfaction stemming from the use of a recommender system

▸ Relevance
  ▸ Additional information may be required in conversational recommenders
  ▸ Explanations can be provided to justify why additional information is needed from the user

Goals when providing explanations (4)

- Comprehensibility
  - Recommenders can never be sure about the knowledge of their users
  - Support the user by relating the user's known concepts to the concepts employed by the recommender
- Education
  - Educate users to help them better understand the product domain
  - Deep knowledge about the domain helps customers rethink their preferences and evaluate the pros and cons of different solutions
  - Eventually, as customers become more informed, they are able to make wiser purchasing decisions
- The aforementioned aims for generating explanations can be interrelated
  - Persuasiveness**+** $\rightarrow$ Trust**-**
  - Effectiveness**+** $\rightarrow$ Trust**+**
  - …

Explanations in general

- *How?* and *Why?* explanations in expert systems
- Form of abductive reasoning
  - Given: $KB \vDash_{RS} i$ (item i is recommended by method RS)
  - Find $KB' \subseteq KB$ s.t. $KB' \vDash_{RS} i$
- Principle of succinctness
  - Find smallest subset of $KB' \subseteq KB$ s.t. $KB' \vDash_{RS} i$
    i.e. for all $KB'' \subset KB'$ holds $KB'' \nvDash_{RS} i$
- But additional filtering
  - Some parts relevant for deduction, might be obvious for humans

Knowledge base

item	score
i7	0.9
i2	0.7
i3	0.3
...	...
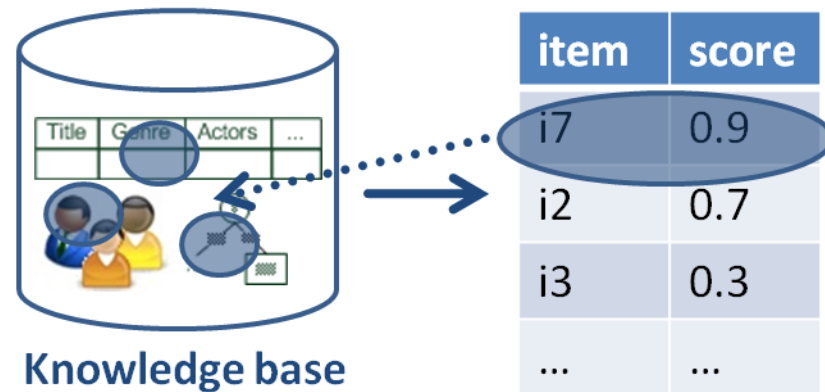
Taxonomy for generating explanations

Major design dimensions of current explanation components:

▸ Category of reasoning model for generating explanations

 ▸ White box

 ▸ Black box

▸ RS paradigm for generating explanations

 ▸ Determines the exploitable semantic relations

▸ Information categories

Paradigm
-Collaborative
-Content-based
-Knowledge-based
-...

Exploited information
categories
-User model
-Recommended item
-Alternatives

Category of reasoning mod
-White box explanations
-Black box explanations
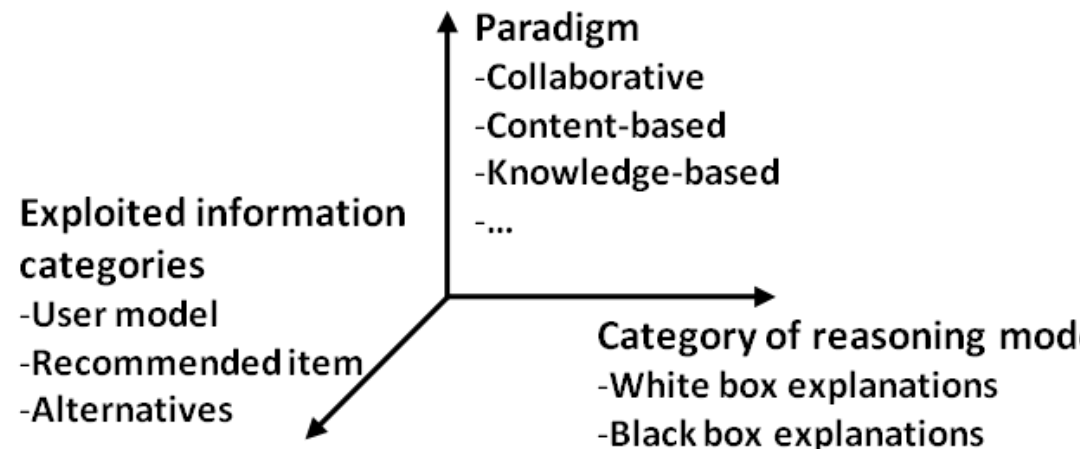
Explanations in CF recommenders

▸ Explicit recommendation knowledge is not available

▸ Recommendations based on CF cannot provide arguments as to why

  ▸ a product is appropriate for a customer or

  ▸ why a product does not meet a customer's requirements

▸ The basic idea of CF is to mimic the human word-of-mouth recommendation process

▸ Therefore, give a comprehensible account of how this word-of-mouth approach works:

  ▸ Customers rate products

  ▸ The CF locates customers with similar ratings (i.e., tastes), called neighbors

  ▸ Products that are not rated by a customer are rated by combining the ratings of the customer's neighbors

Evaluating explanation interfaces
(Herlocker et al. 2000)

▸ Herlocker et al. (2000) examined various implementations of explanation interfaces for the MovieLens Systems

    ▸ Twenty-one variants were evaluated

▸ User study design / questionnaire

    ▸ 21 different explanation approaches

    ▸ Users were asked to rate on a 1-7 scale

        ▸ how likely they would be to go to see a recommended movie given the explanation

    ▸ Base case with no explanation included

    ▸ Additional interface using past performance

        ▸ "MovieLens has provided accurate predictions for you 80% of the time in the past"

Study results

▸ The best-performing explanation interfaces are based on the ratings of neighbors

Movie: XYZ

Your Neighbors` Ratings for this Movie
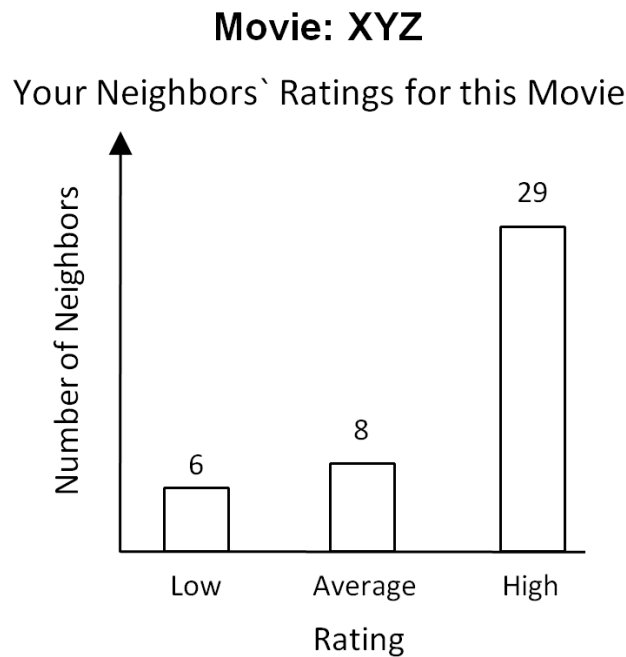
Movie: XYZ

Personalized Prediction: ****

Your Neighbors` Ratings for this Movie

Rating	Number of Neighbors
★	2
★★	4
★★★	8
★★★★	20
★★★★★	9

(Histogram: Number of Neighbors vs Rating — Low: 6, Average: 8, High: 29)

▸ Similar neighbors liked the recommended film, and this was comprehensibly presented.

    ▸ The histogram performed better than the table

Study results

▸ Recommenders using the simple statement about the past performance of MovieLens

  ▸ The second best performer!

▸ Content-related arguments mentioning the similarity to other highly rated films or a favorite actor or actress

  ▸ Among the best performers

▸ Poorly designed explanation interfaces decreased the willingness of customers to follow the recommendation

  ▸ Even compared with the base case

▸ Too much information has negative effects

  ▸ Poor performance was achieved by enriching the data presented in histograms with information about the proximity of neighbors

▸ Supporting recommendations with ratings from domain authorities, such as movie critics:

  ▸ No increase in acceptance

Explanations for CB / KB recommenders

‣ Content-based

　　‣ Properties characterizing items

　　‣ TF*IDF model

‣ Knowledge based

　　‣ Properties of items

　　‣ Properties of user model

　　‣ Additional mediating domain concepts

Content-based techniques

▸ Could be based on item similarity

   ▸ Because you liked …

   ▸ Similar items …

      ▸ Amazon.com's list labels convey explanatory information

▸ Hybrid techniques

   ▸ Combine ratings with content information

      ▸ Keyword-style explanations

      ▸ Tag-based explanations

      ▸ Tag clouds

# Keyword-style explanations

▸ Can be more effective than rating-based ones

Word	Strength	Explain
thriller	36.19	Explain
paris	30.13	Explain
spy	21.28	Explain
action	18.92	Explain
identity	18.72	Expl
conspiracy	16.53	Expl
killer	13.26	Expl

The word action is positive due to the movie ratings:

Movie	Rating	Occurrence
Sin City	5	29
Casino Royale	4	3

"Tagsplanations" and tag clouds
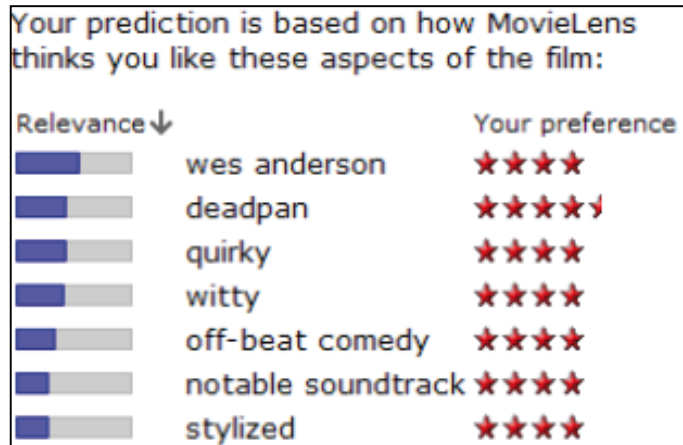
Explanations in case-based RS

▸ The generation of solutions in case-based recommenders is realized by identifying the products that best fit a customer's query

▸ Based on item features and a similarity measure

▸ Each item of a product database corresponds to a case

▸ Customer query puts constraints on the attributes of products

▸ For example, a customer is interested only in digital cameras that cost less than a certain amount of money

Explanations in case-based RS

▸ In particular, given a query Q about a subset A_Q of attributes A of a case (product) description, the similarity of a case C to Q can be defined defined as

$$sim(C, Q) = \sum_{a \in A_Q} w_a sim_a(C, Q)$$

▸ The function $sim_a(C, Q)$

  ▸ describes the similarity of the attribute values of the query Q and the case C for the attribute a

▸ This similarity is weighted by w_a, expressing the importance of the attribute to the customer

▸ A recommendation set is composed of all cases C that have a maximal similarity to the query Q

Explaining solutions (1)

▶ A possible approach to answer a "why-question" is to compare the presented case with the customer requirements

  ▶ highlight which constraints are fulfilled and which are not

▶ Example:

id	price	mpix	Opt-zoom	LCD-size	movies	sound	waterproof
p1	148	8.0	4x	2.5	no	no	yes
p2	182	8.0	5x	2.7	yes	yes	no
p3	189	8.0	10x	2.5	yes	yes	no
p4	196	10.0	12x	2.7	yes	no	yes
p5	151	7.1	3x	3.0	yes	yes	no
p6	199	9.0	3x	3.0	yes	yes	no
p7	259	10.0	3x	3.0	yes	yes	no
p8	278	9.1	10x	3.0	yes	yes	yes

Explaining solutions (2)

▸ If a customer is interested in digital cameras with a price less than 150, then p1 is recommended.

id	price	mpix	Opt-zoom	LCD-size	movies	sound	waterproof
p1	148	8.0	4x	2.5	no	no	yes
p2		8.0	5x	2.7	yes	yes	no
p3	Why?	8.0	10x	2.5	yes	yes	no
p4	196	10.0	12x	2.7	yes	no	yes
p5	151	7.1	3x	3.0	yes	yes	no
p6	199	9.0	3x	3.0	yes	yes	no
p7	259	10.0	3x	3.0	yes	yes	no
p8	278	9.1	10x	3.0	yes	yes	yes

Explaining solutions (3)

▸ ## The weights of the attributes can be incorporated into the answers

  ▸ If the customer requires a price less than 160 and LCD size of more than 2.4 inches, where LCD size is weighted much more than price, then p5 is recommended
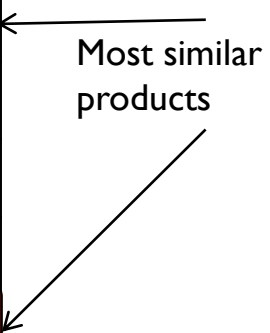
id	price	mpix	Opt-zoom	LCD-size	movies	sound	waterproof
p1	148	8.0	4x	2.5	no	no	yes
p2	182	8.0	5x	2.7	yes	yes	no
p3	189	8.0	10x	2.5	yes	yes	no
p4	196	10.0	12x	2.7	yes	no	yes
p5	151	7.1	3x	3.0	yes	yes	no
p6	199	9.0	3x	3.0	yes	yes	no
p7	2	Why?			yes	yes	no
p8	278	9.1	10x	3.0	yes	yes	yes

Explaining solutions (4)

▸ The requirements of a customer might be too specific

  ▸ Why-explanations provide information about the violated constraints

▸ If the customer requires a price less than 150 and a movie function, then no product fulfills these requirements.

id	price	mpix	Opt-zoom	LCD-size	movies	sound	waterproof
p1	148	8.0	4x	2.5	no	no	yes
p2	182	8.0	5x	2.7	yes	yes	no
p3	189	8.0	10x	2.5	yes	yes	no
p4	196	10.0	12x	2.7	yes	no	yes
p5	151	7.1	3x	3.0	yes	yes	no
p6	199	9.0	3x	3.0	yes	yes	no
p7	259	10.0	3x	3.0	yes	yes	no
p8	278	9.1	10x	3.0	yes	yes	yes

Most similar products

Explaining solutions (5)

▸ p1 and p5 can be considered as most similar products for a given similarity function

  ▸ although one of the user requirements is not satisfied

▸ A why-explanation for p1 would be,

  ▸ "p1 is within your price range but does not include your movie requirement."

▸ Automated techniques can be used to

  ▸ generate minimal sets of customer requirements that explain why no products fit, or to

  ▸ to propose minimal changes to the set of requirements such that matching products exist

Presentation of the explanation

> ▸ Users receive different explanations for each recommended item (here: spa resort)

schließen

Österreich
Längenfeld

» zur Therme

Diese Therme entspricht zu 83% den von Ihnen gesuchten Kriterien
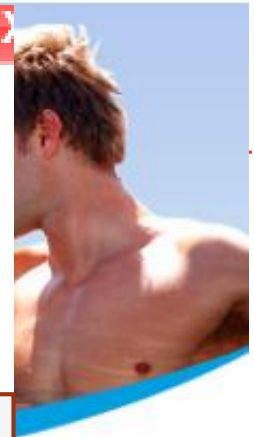
Warum wurde Ihnen diese Therme empfohlen:

Die Therme AQUA DOME - Tirol Therme Längenfeld ist gut für
Familien mit Kindern geeignet. Der Service umfasst unter anderem

It offers services for families with small children, such as X, Y and Z.

...llencenter mit 80m Rutsche, Unterwasserkamera, kostenloser
Kinderanimation und -betreuung.. Spass und Fun kommen bei
Wasserrutschen, Strömungskanal, Wasserfall nicht zu kurz. Die Therme

It is a spa resort of medium size offering around 1000 beds.

Sie erfüllt laut Angaben des Betreibers die geforderten Suchkriterien:
Familie, Fun, Wellness, Kulinarik, Kuscheln. Besonders hervorzuheben

The water has favorable properties for X, but it is unknown if it also cures Y.

...ungen nicht bekannt ist. Kulinarisch bietet sie biologisches
Essen, aber leider nicht wie gewünscht koscheres Essen. Im Detail ist das

It offers organic food, but no kosher food.

Faltenunterspritzungen, Gymnastikprogramme, aber leider nicht wie
gewünscht Hautglättungen.

...Aquarius.
...helfen?

Evaluation

▸ Methodology
  ▸ Online test on real-world platform
    ▸ (see http://www.thermencheck.com)
  ▸ More then 200 participants
  ▸ Randomly division of the participants into two groups:
    ▸ Group A: explanations for the recommendation were shown
    ▸ Group B: no explanation was shown
    ▸ Questionnaire after interaction
  ▸ Questions
    ▸ usability and the use of the system
    ▸ the intention to repeated use,
    ▸ positive usage experience and
    ▸ willingness to recommend to others

Results for the explanation feature

** sign. < 1%, * sign. < 5%
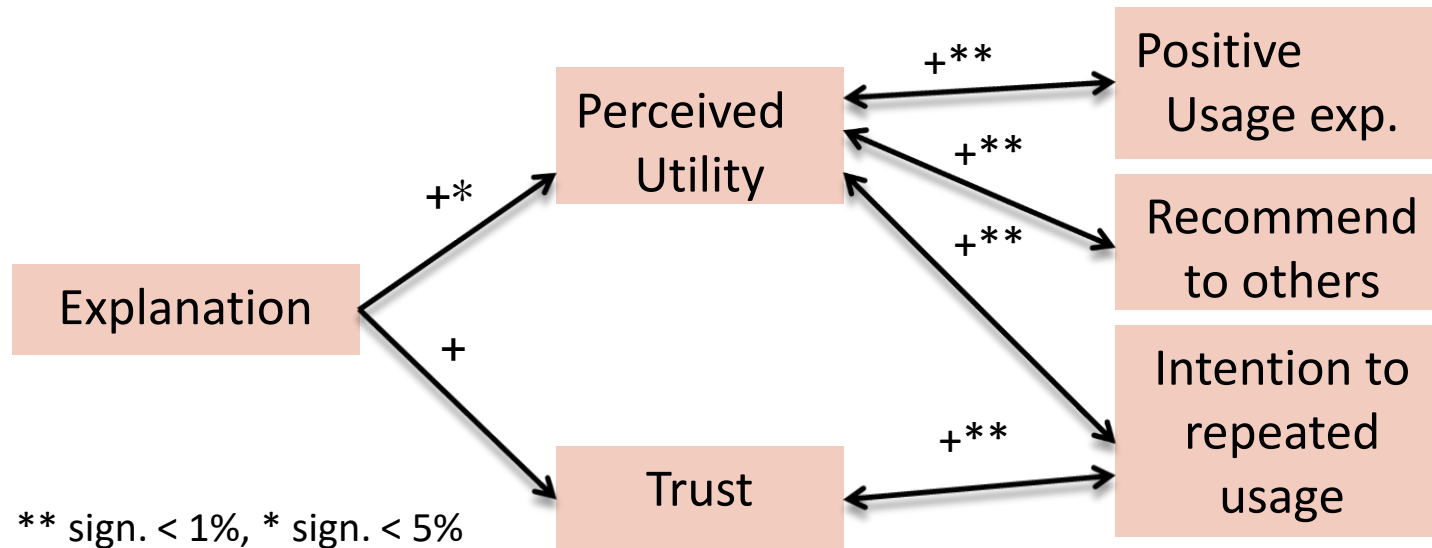
▸ Knowledgeable explanations significantly increase the users' perceived utility

▸ Perceived utility strongly correlates with usage intention etc.