# Explanations in recommender systems

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# Typical system target

# Reality check

- What is the real value of recommender systems?
  - Satisfaction with recommended items, low return rate
- $F_1$ on historical data need not be a good estimate for satisfaction:
  - Recommendation can be self-fulfilling prophecy
    - Users' preferences are not invariant, but can be constructed [ALP03]
  - position/rank matters (e.g. serial position effects)
    - Actual choices are heavily biased by the item's position [FFG+07]
  - inclusion of weak (dominated) items increases users' confidence
    - Replacing some recommended items by *decoy* items fosters choice towards the remaining options [TF09]

# Humans choose poorly

Simplification is an underlying concept of heuristics

- Satisficing
  - Choose the first item that is satisfactory
- Elimination by Aspects
  - Start with the most important attribute
  - Eliminate all item that are not satisfactory
  - Proceed with the next most important attribute
  - Come up with evolved set
- **Reason-based choice**
  - People want to be able to justify their choices
  - May make decisions that are easiest to justify

# Satisficing: SEME

- Study conducted during 2014 Indian general elections

*Epstein & Robertson, PNAS, (2015)*

- About 2000 participants
  - Searched for political news related to Rahul Gandhi, Narendra Modi and Arvind Kejriwal
  - Result display positions were artificially modified to favor searched-for candidate
  - Typical participant spent 5 minutes on the search engine
  - Pre- and post-test questionnaires to measure voting propensity

# Result

| Candidate | Rating | $\chi^2$ | Mean (SE) | | |
|---|---|---|---|---|---|
| | | | Gandhi bias | Kejriwal bias | Modi bias |
| Gandhi | Impression | 3.61 | −0.16 (0.06) | −0.21 (0.06) | −0.30 (0.06) |
| | Trust | 21.19*** | 0.14 (0.06) | −0.04 (0.07) | −0.20 (0.06) |
| | Like | 12.99** | −0.09 (0.07) | −0.17 (0.06) | −0.34 (0.06) |
| | Voting likelihood | 10.79** | 0.16 (0.07) | −0.04 (0.07) | −0.18 (0.07) |
| Kejriwal | Impression | 17.75*** | −0.30 (0.06) | −0.11 (0.06) | −0.39 (0.05) |
| | Trust | 26.69*** | −0.17 (0.07) | 0.15 (0.06) | −0.16 (0.06) |
| | Like | 24.74*** | −0.31 (0.06) | 0.05 (0.06) | −0.23 (0.06) |
| | Voting likelihood | 13.22** | −0.03 (0.06) | 0.17 (0.07) | −0.12 (0.06) |
| Modi | Impression | 24.98*** | −0.22 (0.06) | −0.21 (0.06) | 0.12 (0.05) |
| | Trust | 18.78*** | −0.04 (0.06) | −0.10 (0.06) | 0.23 (0.06) |
| | Like | 16.89*** | −0.16 (0.05) | −0.09 (0.06) | 0.19 (0.06) |
| | Voting likelihood | 31.07*** | −0.07 (0.07) | −0.10 (0.06) | 0.33 (0.06) |

# Other decision-making heuristics

| Phenomenon/Effect | Description |
|---|---|
| Decoy effects | Additional irrelevant (inferior) items in an item set significantly influence the selection behavior |
| Primacy/recency effects | Items at the beginning and the end of a list are analyzed significantly more often/deeply than items in the middle of a list |
| Framing effects | The way in which different decision alternatives are presented influences the final decision taken |
| Priming | If specific decision properties are made more available in memory, this influences a consumer's item evaluations (background priming) |
| Defaults | Preset options bias the decision process |

# Decoy: asymmetric dominance effect

| Product | A | B | D |
|---|---|---|---|
| price per month | 30 | 20 | 50 |
| download limit | 10GB | 6GB | 9GB |

- Product *A* dominates *D* in both dimensions (price and download limit)
- Product *B* dominates alternative *D* in only one dimension (price)
- The additional inclusion of *D* into the choice set often triggers an increase in the selection probability of *A*

# In sum

- Recommender systems are persuasion systems
- People can be persuaded by very flimsy reasons
- Bounded rationality / accuracy-effort-tradeoff makes users susceptible for decision biases
- Presenting justifications is necessary to help people choose for the right reasons

# Why bother with explanations?

Motivation

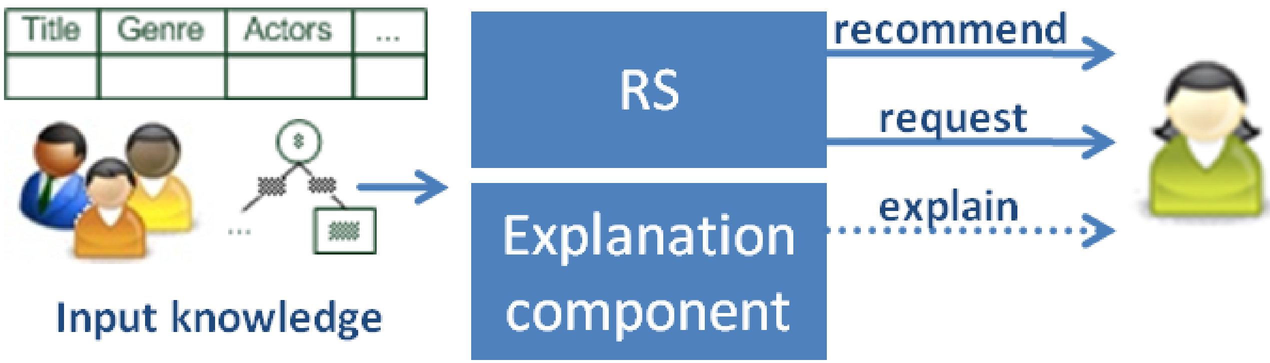
- "The digital camera *Profishot* is a must-buy for you because . . . ."

- Why should recommender systems deal with explanations at all?

- 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 in recommender systems

Additional information to explain the system's output following some objectives



# 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

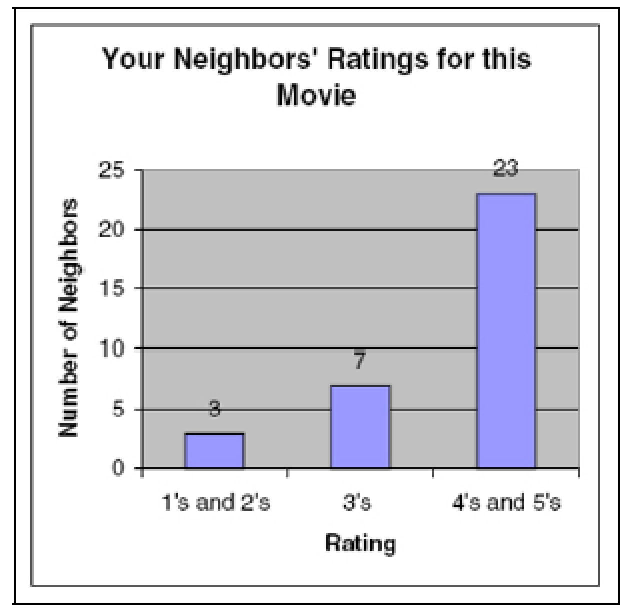
[Friedrich & Zanker, AI Magazine, 2011]

# Evaluating explanations

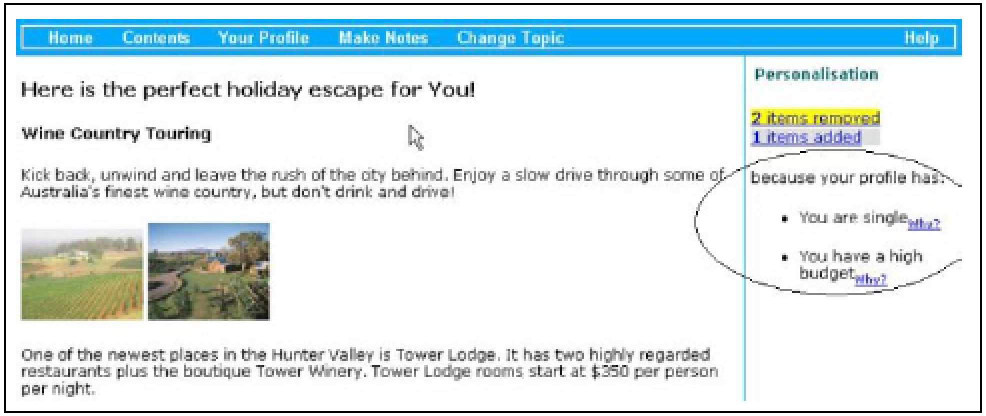
- Transparency (showing its work)
- Scrutability (being understandable and fixable)
- Trustworthiness (in reducing churn)
- Persuasiveness (in making decisions you want)
- Effectiveness (in making good decisions)

# Explanation styles

- Social explanations
- Natural map to CF
- Usually not very persuasive
- Transparent
- Effective



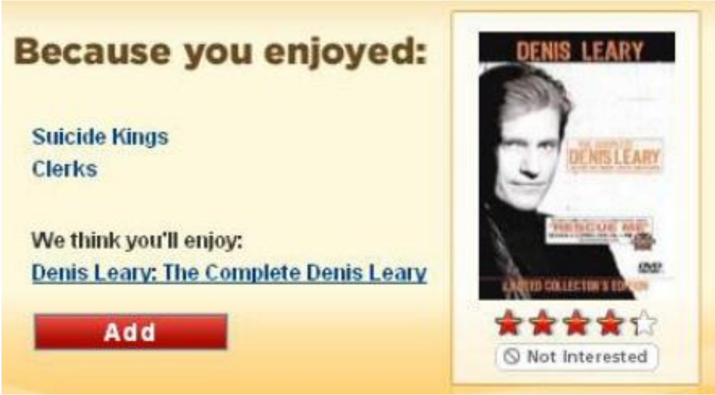
# Content-based



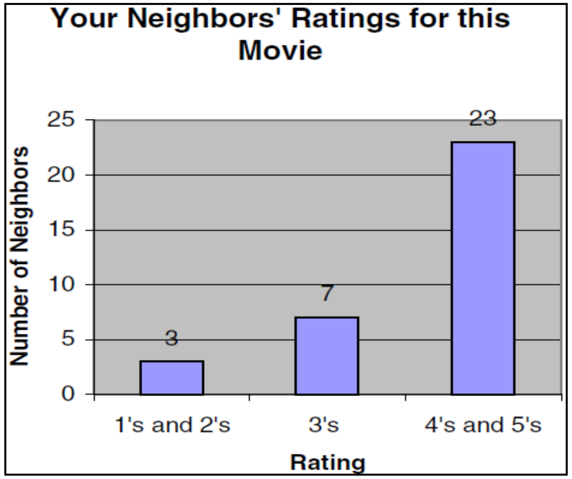


Transparent, scrutable (?), persuasive (?), effective, trustworthy

- Similarity between items




- Similarity between users




- Tags
  - Tag relevance (for item)
  - Tag preference (of user)

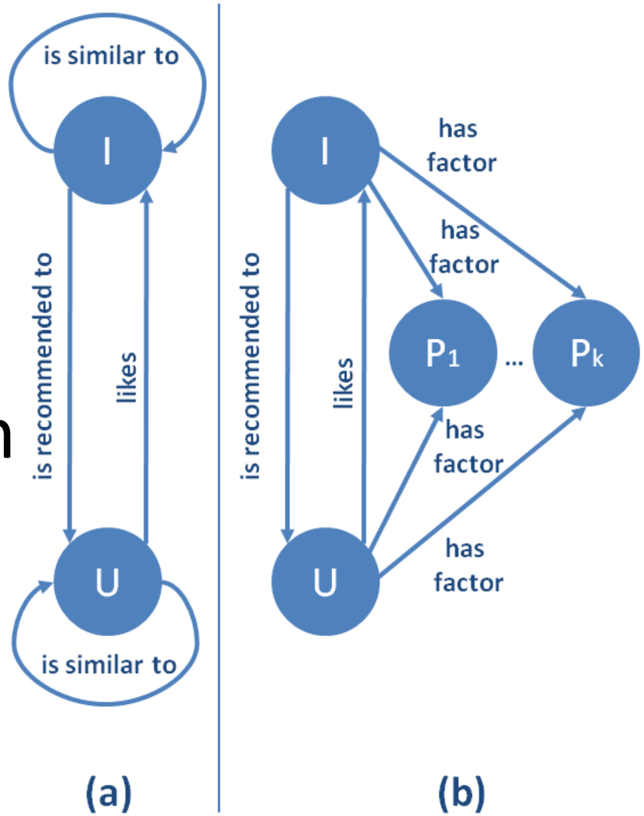
# Knowledge-based explanations

- Vacation example: “This vacation package differs from your requirements only in price, and is otherwise optimal, no matter what duration, location or ambience you select.”
- Trustworthy (?), transparent, scrutable, effective

# RS paradigms and their ontologies

- Classes of objects
  - Users
  - Items
  - Properties
- N-ary relations between them

- Collaborative filtering
  - Neighborhood based CF (a)
  - Matrix factorization (b)
    - Introduces additional factors as proxies for determining similarities



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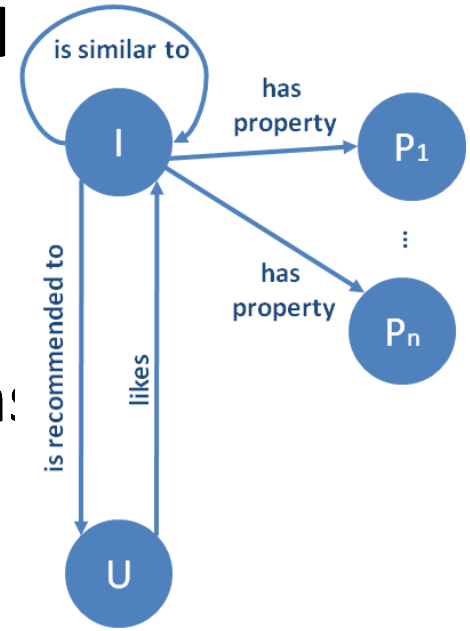
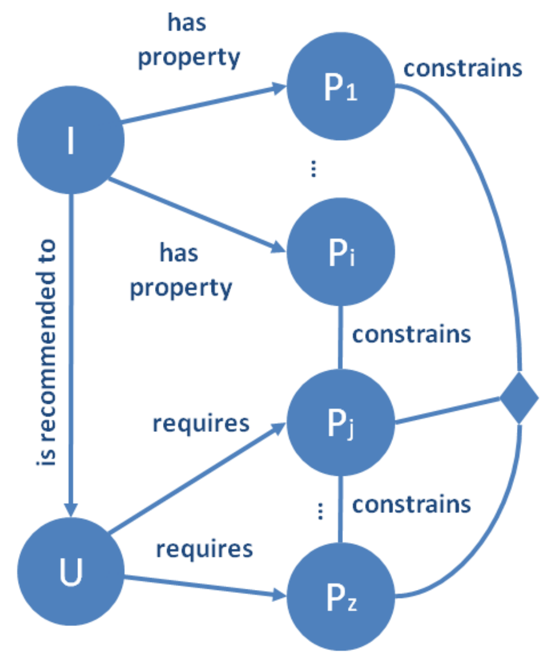
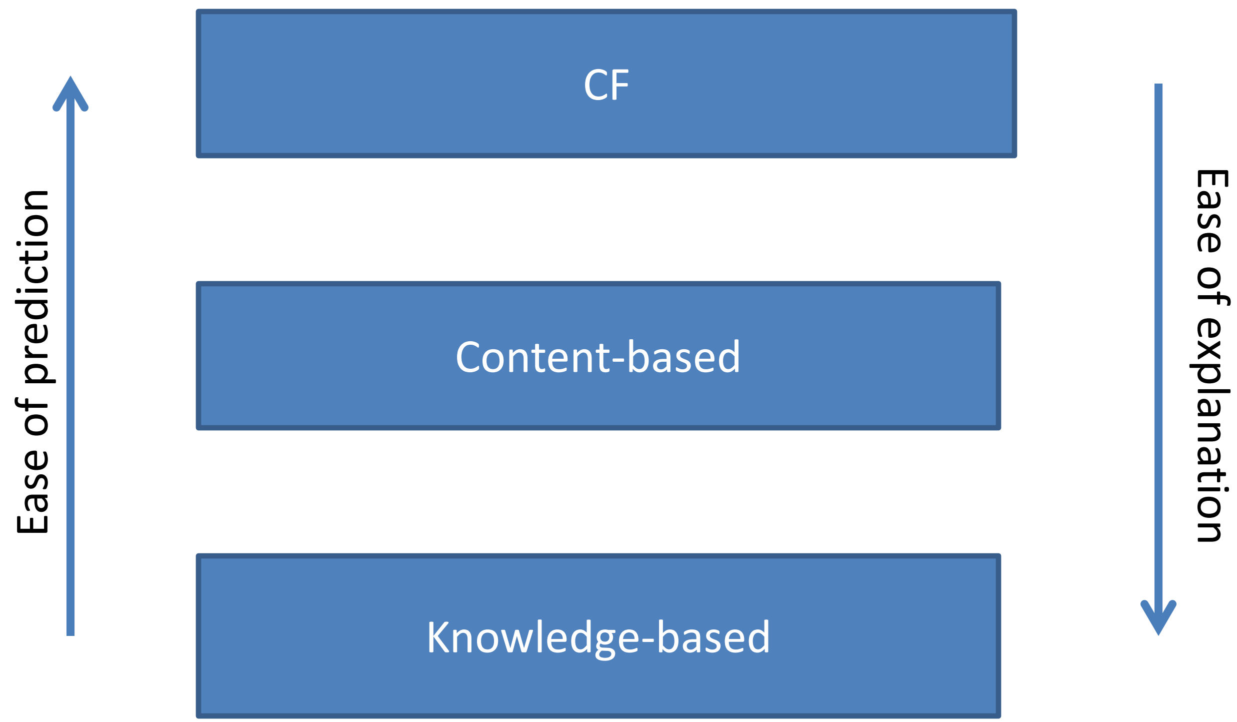



- Content-based
  - Properties characterizing item
  - TF*IDF model

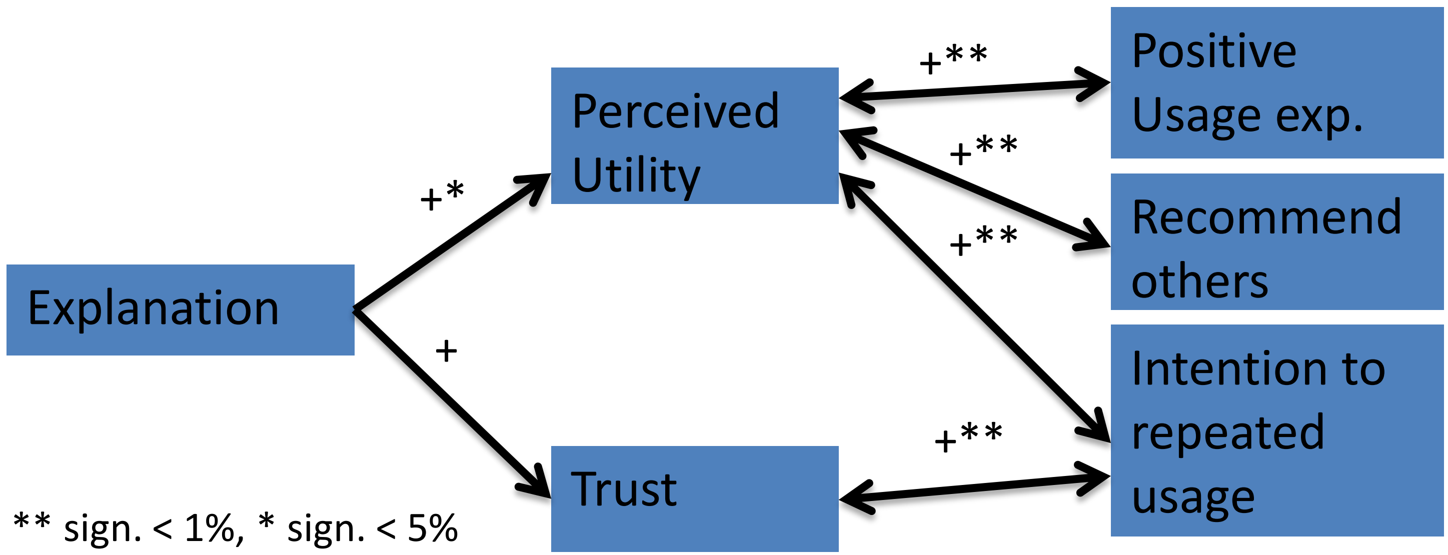



- Knowledge based
  - Properties of items
  - Properties of user model
  - Additional mediating domain concepts

# An important tradeoff



# Results from testing explanation systems




- Knowledgeable explanations significantly increase users' perceived utility
- Perceived utility strongly correlates with usage intention etc.

# Explanations in recommender systems: Summary

- There are many types of explanations and various goals that an explanation can achieve
- Which type of explanation can be generated depends greatly on the recommender approach applied
- Explanations may be used to shape the wishes and desires of customers but are a double-edged sword
  - On the one hand, explanations can help the customer to make wise buying decisions;
  - On the other hand, explanations can be abused to push a customer in a direction which is advantageous solely for the seller
- Understanding explanations and their effects on customers is very important.