International Workshop on Decision Making and Recommender Systems, Bolzano, 2014

Biases in Decision Making

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Agenda

- Recommendation Approaches
- Decision Biases
- Conclusions & Research Issues
Applied Software Engineering Research

Human Decision Making & Recommender Systems
- Group Decision Making
- Group Recommender Systems
- Cognitive (Decision) Biases
- Choicla Environment

Knowledge-based Recommender Systems
- Constraint-based Recommenders
- Speech Recognition Rec.
- Houska Award Nom. (FS)
- WeeVis Environment

Knowledge Engineering (KE)
- Direct & Anytime Diag. (requirements and KBs)
- Knowledge Understanding (Eye-tracking, studies)
- Game-based KE, AIGames
- WeeVis Environment

Software Engineering (SE)
- Recommenders for Requirements Eng.
- Group Recommendation for RE
- Dependency Detection
- IntelliReq Environment
WeeVis Environment

• Provides technologies for the inclusion of recommender applications into Wiki pages.

• Suitable for complex item domains such as computers, financial services, and sports equipment.

• Includes diagnosis and repair functionalities.

• Currently applied by three Austrian universities.

• Freely available: weevis.org
Recommendation Task in WeeVis

- Represented as CSP \((V, D, C)\).
- Variables \(V\) describe customer properties (■) and product properties (□).
- **Compatibility constraints** \(COMP (△)\) define relationships between customer properties.
- **Filter constraints** \(FILT (○)\) describe relationships between customer properties and product properties.
- **Product constraints** \(PROD (●)\) describe the item assortment.
- **Item rankings** are based on utility functions.
- **Customer requirements** \(R (▲)\) are unary constraints on customer properties.
Example: Direct Diagnosis of Inconsistent Requirements

\[ \Delta \subseteq R: \begin{bmatrix} \triangle_1 \ldots \triangle_{k/2} \triangle_{k/2+1} \ldots \triangle_k \end{bmatrix} - \Delta \text{ consistent with } \text{COMP} \cup \text{FILT} \cup \text{PROD} \]

\[ \Delta \subseteq \begin{bmatrix} \triangle_{k/2+1} \ldots \triangle_k \end{bmatrix} \]

„direct diagnosis“ (increase of domain knowledge)


WeeVis MediaWiki Environment
WeeVis MediaWiki Environment

DX14 Demo Recommender

A Tea Recommender for demo purposes

- How much caffeine do you want?
  - no answer

- With additional flavor?
  - no answer

- Do you want to mix it up?
  - no answer

<table>
<thead>
<tr>
<th>Questions</th>
<th>Solutions</th>
<th>Support</th>
</tr>
</thead>
<tbody>
<tr>
<td>How much caffeine do you want?</td>
<td>ChinaGreen Jasmine</td>
<td>100%</td>
</tr>
<tr>
<td></td>
<td>ChinaGreen Superior</td>
<td>100%</td>
</tr>
<tr>
<td></td>
<td>Darjeeling BOP</td>
<td>100%</td>
</tr>
<tr>
<td></td>
<td>Darjeeling SFTGFOP</td>
<td>100%</td>
</tr>
<tr>
<td></td>
<td>EarlGrey</td>
<td>100%</td>
</tr>
<tr>
<td></td>
<td>FruitInfusion</td>
<td>100%</td>
</tr>
<tr>
<td></td>
<td>Herbal Mint</td>
<td>100%</td>
</tr>
</tbody>
</table>
WeeVis MediaWiki Environment

== A Tea Recommender for demo purposes ==

<recommender>
&PRODUCTS
{
  !name!caffeine!drinkWithCat!origin!flavored!#price!
  |FruitInfusion|none|herb|europe|natural|4|
  |Herbal Mint|none|herb|europe|natural|5|
  |ChinaGreen|Jasmine|medium|green|china|jasmine|7|
  |JapanGreen|medium|green|japan|natural|12|
  |ChinaGreen|Superior|medium|green|china|natural|15|
  |Darjeeling|SFTGFOP|medium|dj|india|natural|22|
  |Darjeeling|BOP|strong|dj|india|natural|8|
  |EarlGrey|strong|grey|india|bergamotte|12|
}

&QUESTIONS
{
  |How much caffeine do you want? (none, some, lots)|
  |With additional flavor? (no, yes)|
  |Do you want to mix it up? (plain, lemon, milk)|
  |How much do you want to spend? $(0,25,5,Euro)|

Return to DX14 Demo Recommender.
WeeVis Recommender Applications

• >50 Knowledge Engineers.

• >70 developed Recommenders.

• Interaction logs collected in an anonymous fashion.

• Will be exploited for preference learning.
Heatmap Visualization of Modeling Sessions

- Overview of areas, knowledge engineers looked at.
- Can be used, for example, for constraint ranking.
Choicla Environment

- Decision about new employees, investment decisions, new cars, choosing a restaurant, …
- Modeling environment for decision apps
This Talk …

- Basic introduction to example cognitive biases in the recommender context (100’s exist …)

- Cognitive (decision) biases:
  - “tendency to decide in certain (simplified) ways”
  - can lead to suboptimal decision outcomes

- Bottum-up approach (testing individual biases)
Why Cognitive Biases?

Human brains were not primarily designed for the present time but rather for stone-age conditions

Also: tradeoff between effort and accuracy, maximizers vs. satisficers
Frequent Assumptions …

- Preferences are known/defined beforehand
- Preferences are stable, users don’t change them
- Users have an optimization function in mind

However, preference stability does not exist!
Preferences Are Constructed …

- Not known beforehand
- Often changed
- **No** optimization function used
- Decision heuristics applied (e.g., elimination by aspects)

“Door opener” for **cognitive biases** (tendency to decide in certain ways)!

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Example Influence Factors for Decisions with Recommender Systems

- Ordering of attributes/questions
- Ordering of items
- Configuration of result sets
- Explanation of items
- Presentation context
- Social context

Decision
Examples of Cognitive Biases

<table>
<thead>
<tr>
<th>Theory</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Context effects (decoy effects)</td>
<td>Additional irrelevant (inferior) items in an item set significantly influence the selection behavior</td>
</tr>
<tr>
<td>Primacy/recency effects</td>
<td>Items at the beginning and the end of a list are analyzed significantly more often than items in the middle of a list</td>
</tr>
<tr>
<td>Framing effects</td>
<td>The way in which different decision alternatives are presented influences the final decision taken</td>
</tr>
<tr>
<td>Priming</td>
<td>If specific decision properties are made more available in memory, this influences a consumer's item evaluations</td>
</tr>
<tr>
<td>Defaults</td>
<td>Preset options bias the decision process</td>
</tr>
</tbody>
</table>
Context Effects
Context Effects

- A decision is always made depending on the context in which item alternatives are presented.
- For example, completely inferior item alternatives can trigger significant changes in choice behaviors.
- Example context effects are discussed in the following.
Short Note: Ebbinghaus Effect

- Illusion of relative size perception
- Triggered by context in which objects are shown
- Commonalities with context effects
Context Effects: Overview

- **Compromise**: Target (T) is a compromise to decoy item D (T is *less expensive* and has *slightly lower quality*).

- **Asymmetric Dominance**: T dominates D (T is *cheaper* and has a *higher quality*).

- **Attraction**: T is more attractive than D (T is *slightly more expensive* but has a *higher quality*).
Asymmetric Dominance (D)  
Attraction (D)

expensive

cheap

low quality

high quality

Compromise

Target

Asymmetric Dominance

Attraction
Compromise Effect

<table>
<thead>
<tr>
<th>Product</th>
<th>A (T)</th>
<th>B</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>price per month</td>
<td>30</td>
<td>15</td>
<td>50</td>
</tr>
<tr>
<td>download limit</td>
<td>10GB</td>
<td>5GB</td>
<td>12GB</td>
</tr>
</tbody>
</table>

The addition of alternative $D$ (the decoy alternative) increases the attractiveness of alternative $A$ because, compared with product $D$, $A$ has only a slightly lower download limit but a significantly lower price.

$D$ is a so-called decoy product, which represents a solution alternative with the lowest attractiveness.
Compromise Effect in Financial Services Domain

Study performed with real-world products (konsument.at).

Asymmetric Dominance Effect

<table>
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<td>15</td>
<td>50</td>
</tr>
<tr>
<td>download limit</td>
<td>10GB</td>
<td>5GB</td>
<td>9GB</td>
</tr>
</tbody>
</table>

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 could trigger an increase of the selection probability of A
Asymmetric Dominance Effect

MP3 Player A
- Price: €400
- Storage: 30GB

MP3 Player B
- Price: €300
- Storage: 20GB

MP3 Player C
- Price: €450
- Storage: 25GB
Attraction Effect

<table>
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</tr>
</thead>
<tbody>
<tr>
<td>price per month</td>
<td>30</td>
<td>90</td>
<td>28</td>
</tr>
<tr>
<td>download limit</td>
<td>10GB</td>
<td>30GB</td>
<td>7GB</td>
</tr>
</tbody>
</table>

Product $A$ is a little bit more expensive but of significantly higher quality than $D$.

The introduction of product $D$ would induce an increased selection probability for $A$. 
Calculation of Dominance Values

- Dominance value (DV) of \( d \in \text{Items} \) (includes a decoy D for target item T).

\[
DV_{d \in \text{Items}} = \sum_{i \in \{\text{Items} - d\}} \sum_{a \in \text{Attributes}} \text{weight}_a \times \sqrt{\frac{a_d - a_i}{\max_a - \min_a}} \times \text{sign}(a_d - a_i)
\]

\#\text{Items} - 1

- Reconfiguration problems, e.g., reduce the dominance of T

Impacts on Recommender Systems

- **Faster decisions**: decoys help to resolve cognitive dilemmas in the case of items with the same utility
- **Increased confidence**: decoys serve as a basis for explaining a decision
- **Increased share of specific items**: systematic “push” of target items
- **Diagnosis support**: figuring out which items are responsible for the low share of a target item
- **Interferences between different decoy items** in a set

Primacy/Recency Effects

P → R
Primacy/Recency Effects as a Decision Phenomenon

• Describe situations in which items presented at the beginning and at the end of a list are evaluated significantly more often than others

• Typically, users are not interested in evaluating large lists to identify those that best fit their preferences

• The same phenomenon exists as well in the context of web search scenarios
Item Selection Behavior (Web Links)

- Primacy effect
- Efficacy of the first link
- But also recency
- Tendency to click links at the end

Primacy/Recency Effects as a Cognitive Phenomenon

• Describe situations in which information units at the beginning (primacy) and at the end (recency) of a list are recalled more often than information units in the middle of the list.

• Primacy/recency effects in recommendation dialogs must be taken into account because different dialog sequences can potentially change the selection behavior of consumers.

Primacy/Recency Effects as a Cognitive Phenomenon

• Descriptions at beginning/end of dialog are recalled more often.

• Also in the case “unfamiliar salient” (*), e.g. flyscreen vs. price or weight.

Impacts on Item Selection

Questions $Q_i$ regarding Item Attributes

Attribute order has an impact on perceived attribute importance (e.g., price, weight, …)!

Impacts on Recommender Systems

• **Control of item selections** on the basis of attribute orderings in dialogs

• **Control of diagnosis & repair** and critique selection

• **Users rate items differently** depending on the ordering of argumentations in reviews (ongoing work)

• **Question of debiasing effects** in group decision making (also holds for other biases)

Framing
Framing

- **Framing Effect**: the way a decision alternative is presented influences the decision behavior of the user

- **Example**: 80% lean vs. 20% fat meat

- **Prospect theory**: suggests that potential purchases are evaluated in terms of gains or losses (see “price framing” …)

Price Framing: Example

Which company would you purchase wood pellets from, X or Y?

- **Company X** sells pellets for **€24.50** per 100kg, and gives a **€2.50 discount** if the customer pays with cash
- **Company Y** sells pellets for **€22.00** per 100kg, and charges a **€2.50 surcharge** if the customer uses a credit card

Company **X rewards buyers** with a discount, which is considered a gain (we want to avoid losses …)

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Impacts on Recommender Systems

- **Positive framing** increases selection probability (e.g., 95% no loss vs. 5% loss) → use graphical representation …

- **Price framing**: potential shift from quality to secondary attributes (e.g., payment services)

- Low impact of secondary attributes in all-inclusive offers

- Not every item property is equally salient at decision time
Priming
Priming

- Idea of making some properties of a decision alternative more accessible in memory such that this setting will directly influence user evaluations

- Def. Influencing of the processing of a current stimulus by the activation of already memorized knowledge by a precedent stimulus

- Example: background priming exploits the fact that different page backgrounds can directly influence the decision-making process
Background Priming

Cloudy background triggered users feelings of comfort and caused users to select more expensive products (focus on quality attributes)


Further Effects
Defaults

• People tend to favor the status quo compared to other decision alternatives (“status quo bias”)

• People are typically loss-averse (prospect theory)

• If defaults are used, users are reluctant to change predefined settings (mistakes, additional effort, …)

• Defaults can be used, for example, to …
  • Influence decisions (ethical issues!)
  • Reduce the overall interaction effort and actively support consumers in the product selection process
Defaults: Example

Anchoring

- Tendency to rely too heavily on the first information (anchor) within the scope of decision making
- Ratings biased to be higher result in higher ratings of the current user
- Example: ratings in collaborative filtering, preferences articulated by the first group member


Group Decision Support in Requirements Engineering (RE)

- Study @ TU Graz: 40 Software teams with ~ 6 members.
- Group recommendation support for RE processes
- Group recommendations significantly increase the degree of information exchange between users
- Hidden preferences increase dissonance between stakeholders but increase perceived decision support quality

Conclusions

• Preferences are not known beforehand and often changed (☞ “preference construction”)

• Decisions are not based on optimization functions but on different types of decision heuristics (also occur in patterns of choosing)

• Different decision biases can occur (decoy effects, serial position effects, framing, etc.)

• Have to be taken into account in RS development

• Many open research issues …
Research Issues

- Investigation of decision biases in groups
- Consensus-fostering recommendations
- Debiasing recommendations (e.g., in CF)
- Fairness in decision processes in the long run
- Choicla decision support based on recommendation technologies (www.choicla.com)
Thank You!
References


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