TU Graz

PeopleViews: Human Computation for Constraint-Based Recommendation

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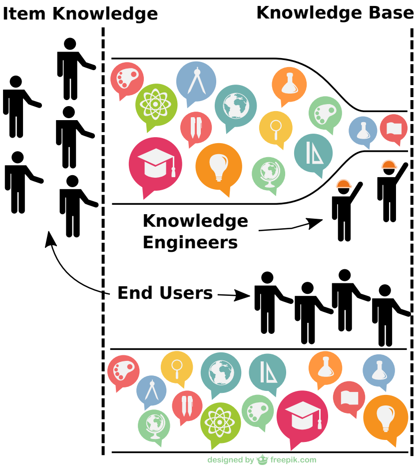
Contents

Constraint-based Recommendation

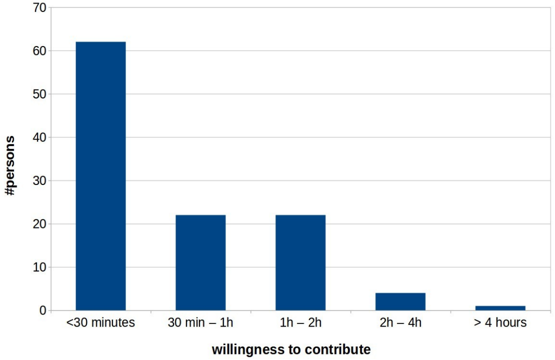
- Specific type of knowledge based recommendation
- Relies on a predefined set of constraints
- Rankings determined by utility function
- Why constraint-based recommendation?
  - Suitable for complex item domains
  - Possible to „explain“ recommendations
  - Diagnoses for too strict requirements

Knowledge acquisition bottleneck

- Only a few Knowledge Engineers
- Possibly a lot of users with item knowledge
- Idea: enable users to contribute to knowledge bases
- Are users willing to contribute to knowledge bases?



How willing are end users to contribute?



N=161, 111 would be willing to contribute

[Felfernig et al., CrowdRec 2014]

PeopleViews

- Short-term tasks (*Micro-tasks*)
  - Domain experts perform short-term knowledge engineering tasks they are much better in compared to knowledge engineers.
- Potential advantages
  - Less effort related to recommendation knowledge base development and maintenance
  - Fewer erroneous constraints
  - Significantly higher degree of scalability

PeopleViews - Knowledge base

- Product attributes
  - „Facts“ about items, e.g. sensor size of a camera
  - Defined when item is added to knowledge base
- User attributes
  - Perceived differently by users, e.g. a cameras field of application
  - Defined by users in micro tasks
- Support
  - Support of item for specific {user, product} attribute value

PeopleViews - Features

Users are able to:

- Define new knowledge bases
  - Create new recommendation domain
  - Add items to existing domains
  - Evaluate existing items
  - „Answer“ micro tasks
- Use existing knowledge bases to get recommendations

Definition of knowledge bases

Product attributes

attribute	question to user	domain	similarity metric
sensorsize	Preferred sensor size?	{fullframe, APS-C, MFT, 1“, 2/3“}	EIB
max-shutterspeed	Required max. shutter speed?	{1/4000, 1/6000, 1/8000, 1/16000}	LIB
maxISO	Required max. ISO sensitivity?	{6400, 12800, 25600}	MIB
price	Max. price?	integer	LIB

Definition of knowledge bases

Product attributes

sensorsize | Enumeration | Exact match | Remove

Preferred sensor size?

☑ Usable as recommendation filter

Possible answers

fullframe x | APS-C x | MFT x | 1" x | 2/3" x

price | Number | Less is better | Remove

Max. Price?

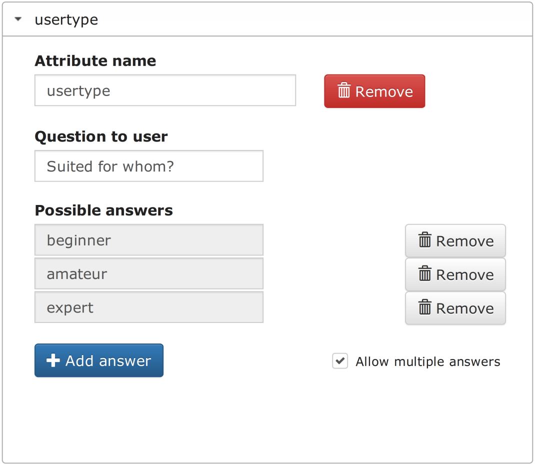
☐ Usable as recommendation filter

Definition of knowledge bases

User attributes

attribute	choice type	question to user	domain
usertype	multiple	Suited for whom?	{ beginner, amateur, expert }
application	single	Preferred application?	{ sport, architecture, macro, landscape, portrait }
usability	single	Minimum accepted usability?	{ average, high, very high }

Definition of knowledge bases



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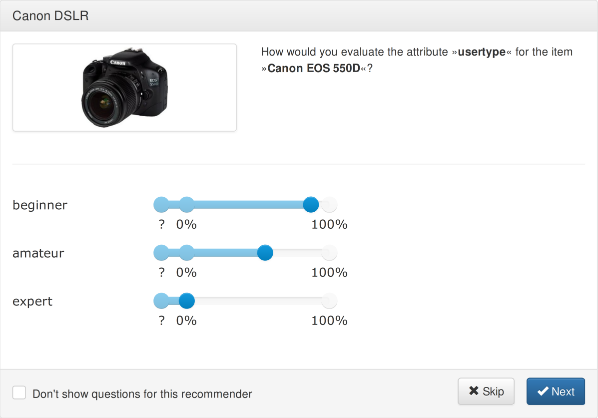
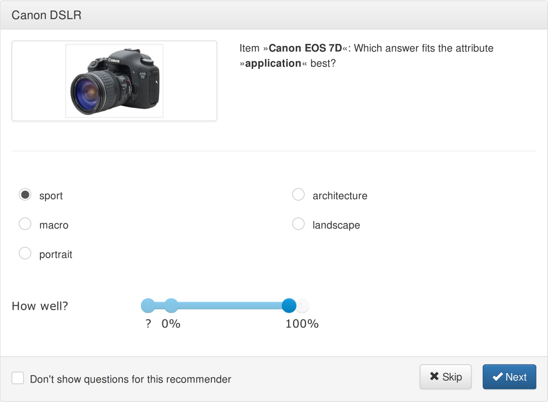
Micro-tasks



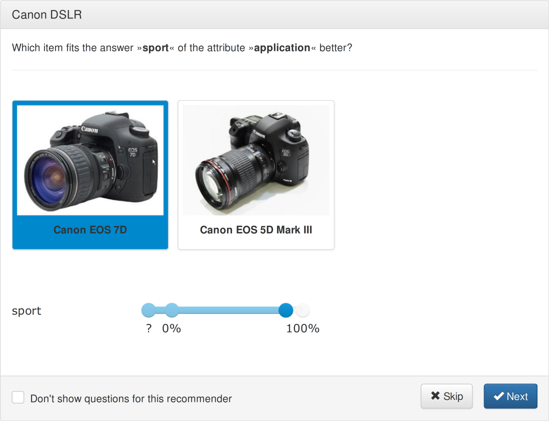
choice type: multiple

Micro-tasks



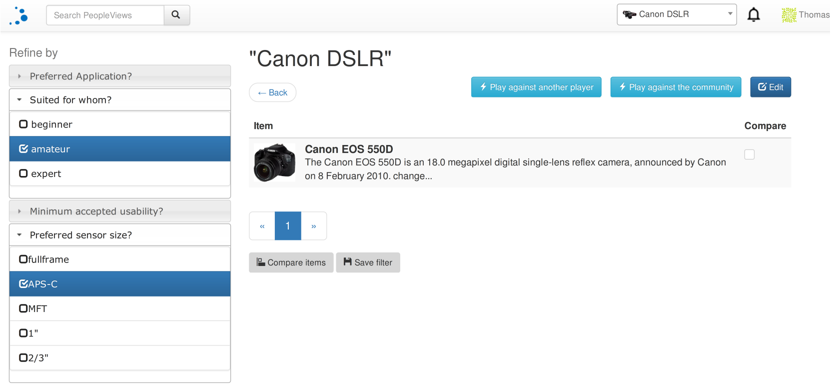
choice type: single

Micro-tasks

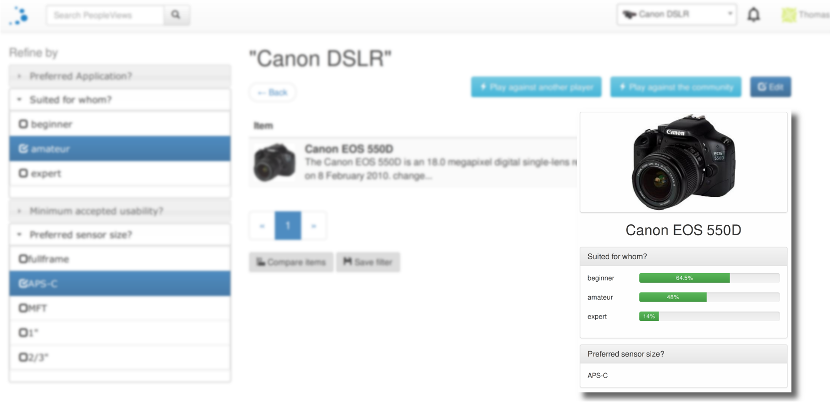


choose item, single attribute

Recommendation view



Recommendation view - Item details



Recommendation approach in PeopleViews

User attributes

$$support(\Phi, u, v) = \frac{\sum s(\Phi, u, v)}{|s(\Phi, u, v)|} \cdot \frac{|s(\Phi, u, v)|}{|s(\Phi, u)|}$$

symbol	meaning
Φ	item
u	user attribute u $\in$ U
p	product attribute
v	{user, product} attribute value
s(Φ, u, v)	support specified by user

Recommendation approach in PeopleViews

Product attributes

$$support(\Phi, p, v) = \begin{cases} \text{1if v = val}(\Phi\text{, p), 0 otherwise} & \text{EIB} \\ 1 - \dfrac{|\text{v - val}(\Phi\text{, p})|}{\text{max}(\Phi\text{, p) - min}(\Phi\text{, p})} & \text{NIB} \\ \dfrac{\text{val}(\Phi\text{, p)-min}(\Phi\text{, p})}{\text{max}(\Phi\text{, p) - min}(\Phi\text{, p})} & \text{MIB} \\ \dfrac{\text{max}(\Phi\text{, p)-val}(\Phi\text{, p})}{\text{max}(\Phi\text{, p) - min}(\Phi\text{ ,p})} & \text{LIB} \end{cases}$$

Recommendation approach in PeopleViews

Selection of recommendation-relevant items

$$\mathrm{f}(\Phi) = \bigwedge_{u \in U} u \in \mathrm{values}(\Phi, \mathrm{u}) \cup \{noval\} \rightarrow \mathrm{include}(\Phi)$$

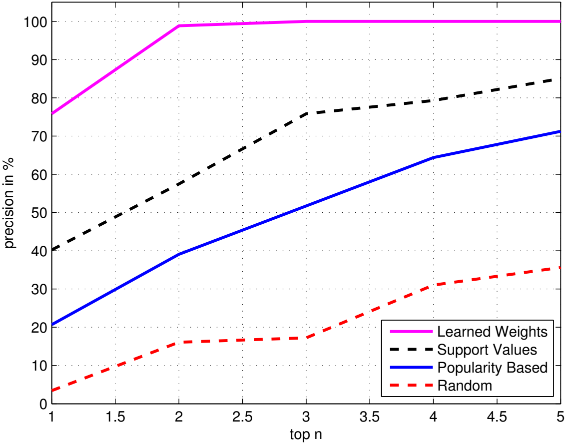
Ranking items by their utility

$$\mathrm{utility}(\Phi, \mathrm{REQ}) = \sum_{a=v \in REQ} \mathrm{support}(\Phi, \mathrm{a}, \mathrm{v}) \cdot w(a)$$

Evaluation of recommender algorithms

- Collect data using WeeVis (http://www.weevis.org)
- Canon DSLR recommender
  - 16 items, 7 attributes (27 possible „answers“)
- Users defined their requirements and selected best matching camera
- 356 unique sessions
- 1 out of N „training and evaluation“
- Is desired item in top n recommended items?

Comparison to other approaches



Ongoing and future work

- Recommendation approaches
  - Implementation and evaluation of further approaches; diagnoses and repair
- Micro-task scheduling
  - Automatically assign micro-tasks to users, using a content-based approach
- Quality assurance
  - Improve dataset quality and prevent manipulation

Thank you!