Using Collaborative Filtering to Enhance Domain-Independent CBR Recommender’s Personalization

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Research Topic

- Due to the increasing competition and the e-users that are becoming more and more picky, the situation has never been more challenging for the e-commerce

- Integration of personalized recommendations to improve the user’s experience

Our goal:
- Generate recommendations as personalized as possible
- Design a domain-independent recommender system

Our solution:
- Case-Based Reasoning for contextualized recommendations
- Collaborative Filtering for more personalized recommendations
Outline

- Domain-Independent Recommender
  - Case-Based Reasoning
  - Related Work
  - Our Domain-Independent CBR Recommender

- Personalization of the Recommendations
  - Collaborative Filtering
  - Proposed Hybridization Strategy
  - Experimentation Results

- Conclusion

- Future Work
Domain-Independent Recommender
Case-Based Reasoning (CBR)

- Problem solving & active learning methodology
- Reuses previous similar experiences (Cases) to resolve a new problem
- Case=\langle Problem, Solution, Result \rangle
CBR for Recommendation

- Introduced to the recommendation field as a knowledge-based filtering technique

- In a recommendation scenario:
  - Problem = attributes of the request, environment and context knowledge, user profile
  - Solution = recommended item
  - Result = user’s feedback

- One remaining issue: **Domain dependence**
Related Work

- CBR tools and frameworks that facilitate the development of CBR applications (CBR*Tools, myCBR, jCOLIBRI)

- FIONN (D. Doyle & al. 2005): a framework allowing the exchange of structured data over CBR systems

- CBROnto (B. D´ıaz-Agudo & al. 2002): an ontology formalizing CBR solving methods as well as the required knowledge to apply them
Our Domain-Independent CBR Recommender

IEEE RCIS'15 -- Using Collaborative Filtering to Enhance Domain-Independent CBR Recommender's Personalization
Personalization of the Recommendations
Collaborative Filtering

- Based on the assumption that other users opinions can be aggregated to generate a reasonable prediction of the active user’s preference.

- Generally relies on the preferences history of the users to generate the recommendations ➔ Domain independent

- Matrix factorization techniques: perform better than traditional CF algorithms (Ref. works of Yehuda Koren)
  - We use an SVD-Based algorithm
Proposed Hybridization Strategy

\[ S_{CF+CBR} = \frac{S_{CBR} + S_{CF}}{2} \]
Experimentation Results

- Basic recommendations scenario: Suggestion of restaurants taking into account the search criteria of the user

- Restaurants Data Set (Available online*)
  - 130 Restaurants
  - 21 nominal & numeric attributes
  - 1161 ratings
  - 138 users
  - Ratings scale: 0 (Bad) – 2 (Good)

* http://archive.ics.uci.edu/ml/datasets/Restaurant+%26+consumer+data
Experimentation Results

- Similarity Knowledge

- Case structure
Exemple of a user’s request
Experimentation Results

- Top-10 recommended items using the CBR recommender

<table>
<thead>
<tr>
<th>Id</th>
<th>Ambiance</th>
<th>Cuisine</th>
<th>Opening</th>
<th>City</th>
<th>Pkg</th>
<th>Payment</th>
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Experimentation Results

- Predicted ratings of the recommended items using collaborative filtering

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Personalized recommendations using the hybrid recommender

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</table>
Conclusion

- Domain-Independent Reasoning
- Easily adaptable to any recommendation scenario
- CBR retrieves the items that meet the user’s needs and context
- Collaborative Filtering re-orders the recommendations list based on the preferences history of the users
Future Work

- Recommendation of compound items by integrating the adaptation step of CBR
- Integration of collaborative filtering in the adaptation process to compose personalized items
- More thorough evaluation of the approaches using an adapted and consistent data set
- Distribution of the system to improve the execution performances
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http://www.mycoachnutrition.com
Thanks for your attention
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