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

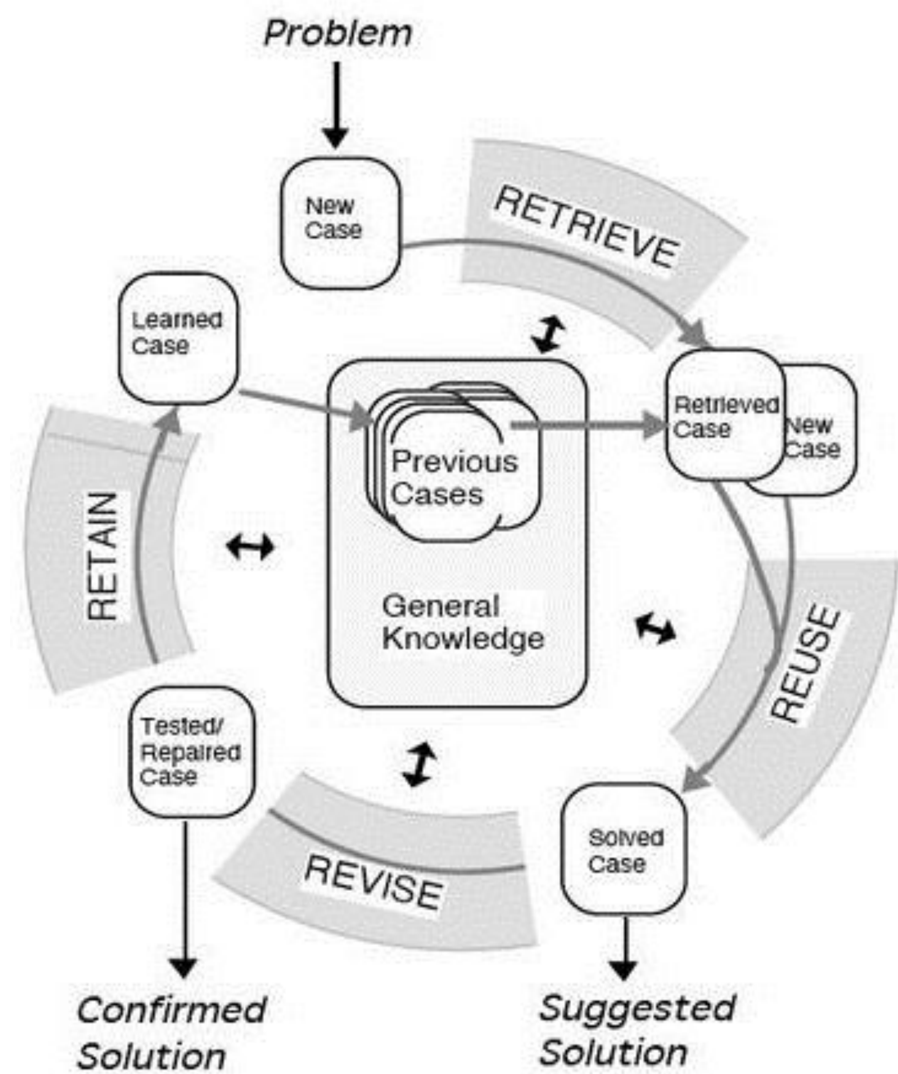
Outline

- Domain-Independent Recommender
  - Case-Based Reaosning
  - Related Work
  - Our Domain-Independent CBR Recommender
- Personalization of the Recommendations
  - Collaborative Fitlering
  - Proposed Hybridization Strategy
  - Experiementation 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=<Problem, Solution, Result>



CBR for Recommendation

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

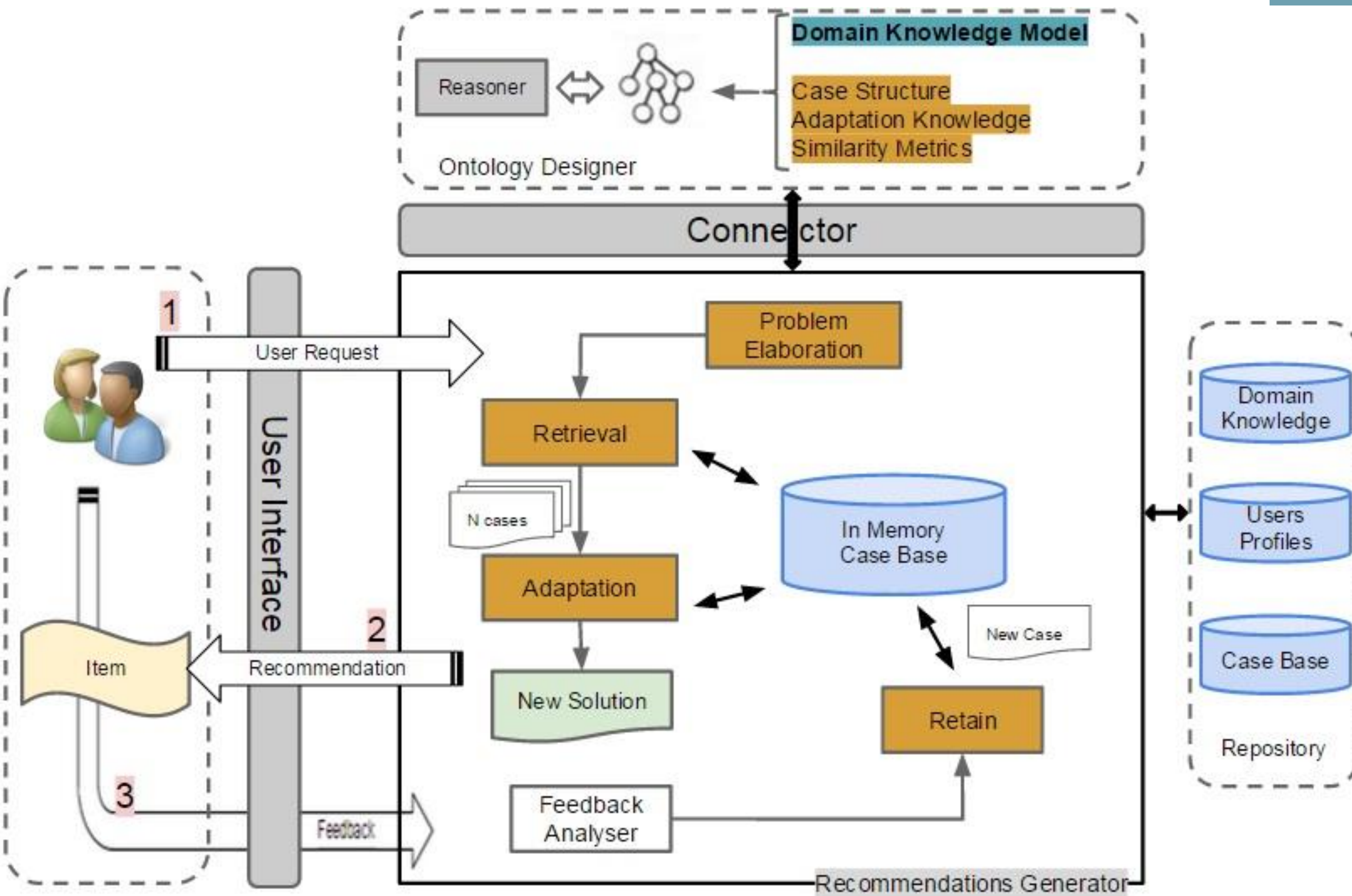
- In a recommendation scenario:
  - Problem = attributes of the request, environment and context knowledge, user profile
  - Solution = recommended item
  - Result = user's feedback

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

Related Work

- CBR tools and frameworkd that faciliate 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



Personalization of the Recommendations

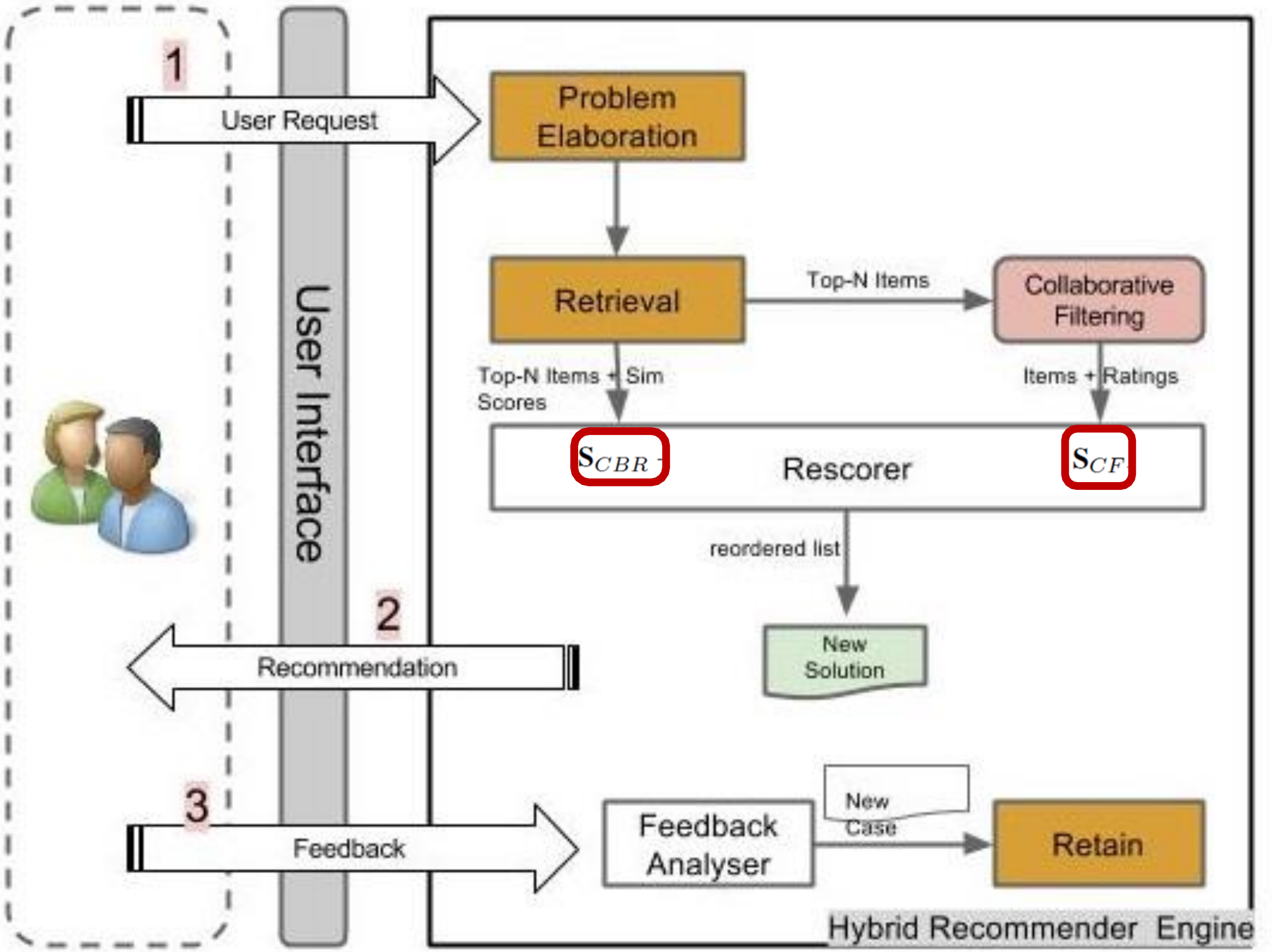
Collaborative Filtering

- 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



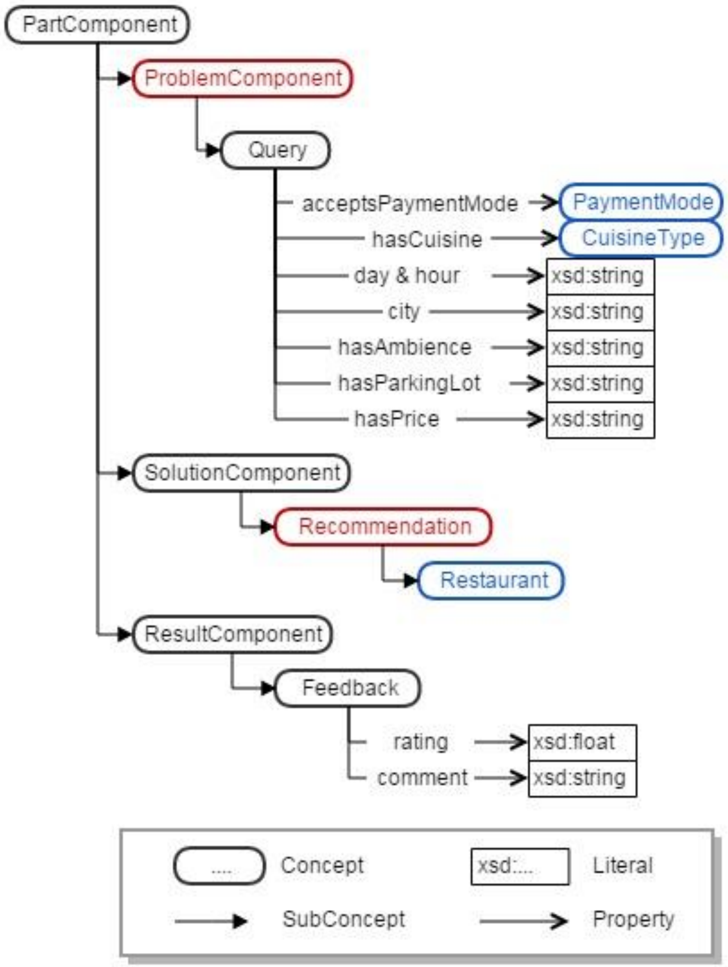
$$\mathbf{S}_{CF+CBR} = \frac{\mathbf{S}_{CBR} + \frac{\mathbf{S}_{CF}}{\mathbf{R}}}{2}$$

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 attribuites
  - 1161 ratings
  - 138 users
  - Ratings scale: 0 (Bad) – 2 (Good)

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

Experimentation Results



- Case structure

Attribute	evaluatedUsingLocalSim	hasWeight
date & hour	timeComparator	0.4
city	ExactSim	0.3
hasCuisine	ListsComparator	0.1
hasPrice	Matrix	0.1
acceptsPaymentMode	ListsComparator	0.05
hasAmbience	ExactSim	0.025
hasParkingLot	ListsComparator	0.025

- Similarity Knowledge

Experimentation Results


```
{
  "Problem":{
    "Restaurant":{
      "hasAmbience":"familiar",
      "hasCuisine":"http://www.kiolis.com/projects
      /fiora/ontologies/restaurants.owl#cuisine_23
      ",
      "openingHours":"weekDay + 18:00",
      "city":"San Luis Potosi",
      "hasParkingLot":"public",
      "acceptsPaymentMode":"http://www.kiolis.com/
      projects/fiora/ontologies/restaurants.owl#pa
      ymentmode_11",
      "hasPrice":"medium"
    }
  }
}
```


- Exemple of a user's request

Experimentation Results

	Id	Ambiance	Cuisine	Opening	City	Pkg	Payment	Price
1	135085	familiar	23	00:00 to 00:00	SLP	public	11	medium
2	135086	familiar	23, 32	08:00 to 23:00	SLP	yes	11, 3, 4	medium
3	135046	familiar	23	08:30 to 21:00	SLP	yes	11, 3, 4	medium
4	135082	familiar	-	10:00 to 18:00	SLP	-	11	medium
5	135033	familiar	-	09:00 to 21:00	SLP	-	11, 4, 3, 1	medium
6	135063	familiar	-	08:30 to 19:30	SLP	-	11	medium
7	135081	familiar	-	14:00 to 23:30	SLP	-	11, 4, 3	medium
8	135070	familiar	-	07:00 to 23:00	SLP	yes	11	medium
9	135062	familiar	-	00:00 to 23:30	SLP	yes	11	medium
10	135053	familiar	23, 12, 33	11:00 to 22:00	SLP	yes	11, 3, 4	high

- Top-10 recommended items using the CBR recommender

Experimentation Results

	ID Restaurant	Rating U1024	Rating U1134	Rating U1071
1	135085	1.10	**2.0**	**1.72**
2	135086	-	1.64	-
3	135046	1.17	**2.0**	-
4	135082	-	-	-
5	135033	-	-	1.0
6	135063	**1.53**	-	**2.0**
7	135081	1.28	-	0.88
8	135070	-	-	-
9	135062	**1.57**	1.61	1.55
10	135053	-	-	-

- Predicted ratings of the recommended items using collaborative filtering

Experimentation Results

	U1024		U1134		U1071	
	Hybrid	*CBR rank*	*Hybrid*	*CBR rank*	*Hybrid*	*CBR rank*
1	135063	**6**	135085	1	135085	1
2	135062	**9**	135046	3	135063	**6**
3	135081	**7**	135086	2	135062	**9**
4	135046	3	135062	**9**	135033	5
5	135085	1			135081	**7**

- Personalized recommendations using the hybrid recommender

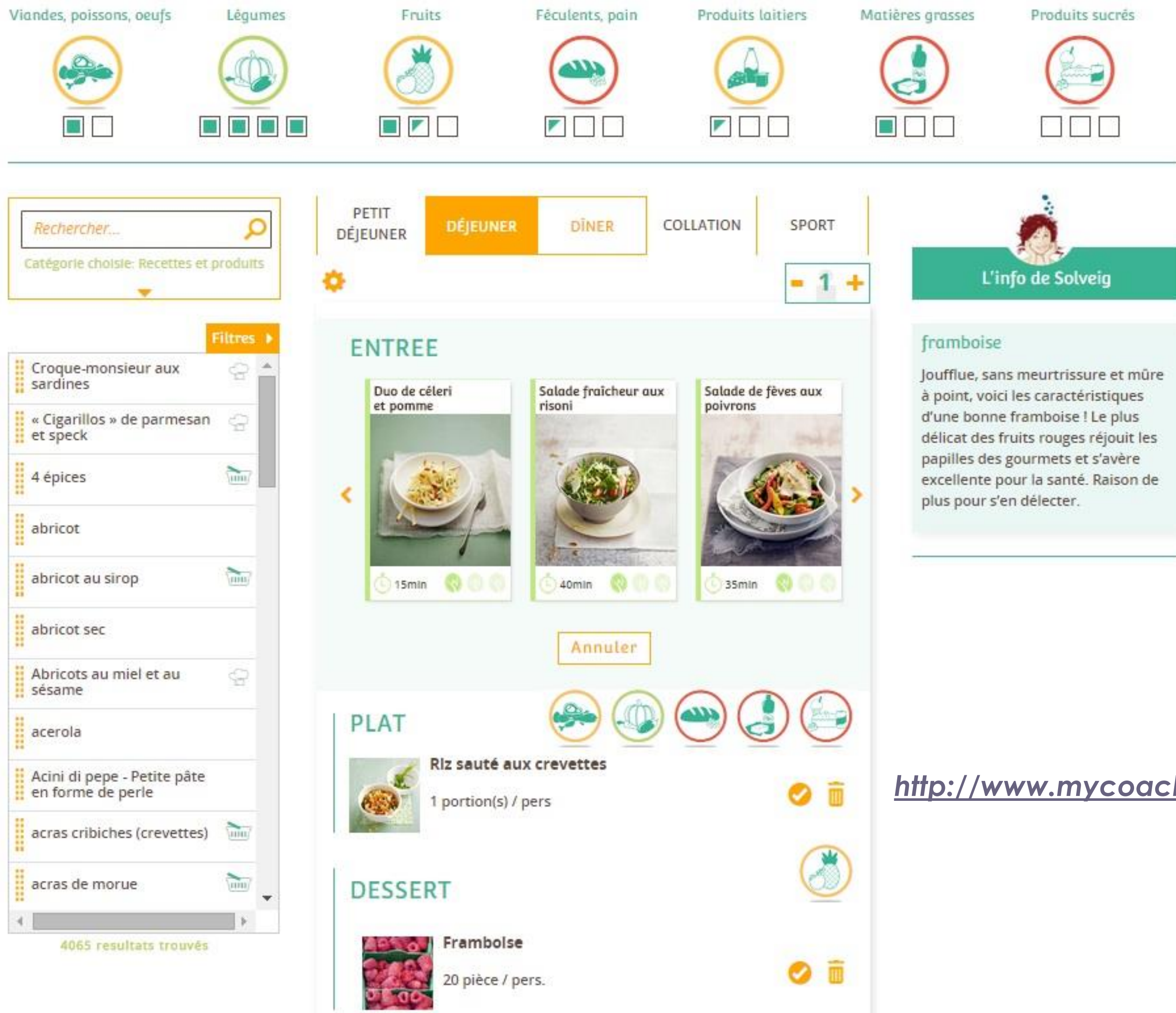
Conclusion

- 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

Future Work



http://www.mycoachnutrition.com

Thanks for your attention

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