Show Me Your Friends, I'll Tell You Who You Are: Recommending Products Based on Hidden Evidence

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Motivation

- Thousands of new products enter the market everyday. Collaborative recommender systems suffer from cold start.
- Recommender systems based on Conversational Case-Based Reasoning (**CCBR-RSs**) assume no prior knowledge about the user.

Objective

To improve the efficiency of a CCBR-RS by mining evidence using limited feedback provided by the user

Evidence

"One or more reasons for believing that something is or is not true" [1]
"Evidence is the data that a system collects which can be used to understand what the user likes, and what the system should recommend in the future." [2]

Conversational Case-Based Reasoning Recommender Systems

Recommendation Phase

	Price(Rs. in Thousands)	Top Speed(Kmph.)	Mileage(Kmpl.)
Query	-	-	**55**
P3	50	125	55
P1	80	150	50
P6	75	145	40

Table 1: Example Motorcycle Domain with Query and Recommendations

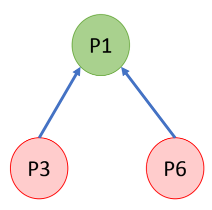
Feedback Phase: Preference-based Feedback (PBF)

	Price(Rs. in Thousands)	Top Speed(Kmph.)	Mileage(Kmpl.)
P3	50	125	55
P1	80	150	50
P6	75	145	50

Table 2: Example Motorcycle Domain preference feedback

New Query: P1

Evidence from feedback



User Preferred Products (**UPP**): {P1}
User Rejected Products (**URP**): {P3, P6}
User Dominance Relations (**UDR**): {(P1,P3), (P1,P6)}
$\forall\, R \in$ **UDR**, $R = (R_d, R_r)$
R_d: Dominant product R_r: Rejected product

Trade-offs

- Trade-off is the compromise made on certain attributes for the sake of desirable values in other attributes.

Trade-offs Representation [3]

	price(Rs. in Thousands)	top speed (kmph)	mileage (kmpl)
P3	50	125	55
P1	80	150	50
P6	75	145	50
T_{P1P3}	-1	1	-1
T_{P1P6}	-1	1	0

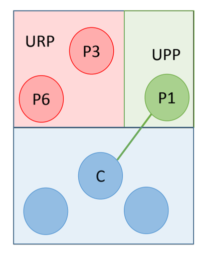
- T_{P1P6} Dominant Set: {top speed}; Dominated Set: {price}

Similarity between trade-offs

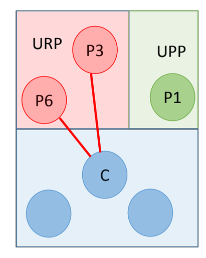
$$tradSim(T1,T2) = \frac{\sum_{a \in Attributes} \mathbf{1}(T1_a = T2_a)}{|Attributes|} \qquad (1)$$

	price(Rs. in Thousands)	top speed (kmph)	mileage (kmpl)
T_{P1P3}	-1	1	-1
T_{P1P6}	-1	1	0
tradSim(T_{P1P3}, T_{P1P6})	(1+1+0)/3 = 0.67		

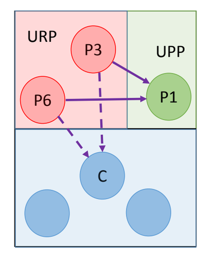
Exploiting evidence from PBF



Observation 1:
The more similar the candidate **C** is to the products in **UPP** the higher the utility. The higher the sim(C, P1) value, the higher the utility of **C**.



Observation 2:
The more similar the candidate **C** is to the products in **URP** the lesser the utility. The higher the sim(C, P3) + sim(C, P6) value, the lower the utility of **C**.



Observation 3:
The more similar the trade-offs a user has to make in choosing candidate **C** over products in **URP** is to the trade-offs the user has made (the trade-offs in **UDR**) the higher the utility. The higher the *tradSim*(T_{P1P3},T_{CP3}) + *tradSim*(T_{P1P6},T_{CP6}) value, the higher the utility of **C**.

Formulation:

$$Score(C,UPP,URP,UDR) = \alpha * \frac{\sum_{A \in UPP} sim(C,A)}{|UPP|} - \beta * \frac{\sum_{B \in URP} sim(C,B)}{|URP|} + \gamma * \frac{\sum_{R \in UDR} tradSim(T_{R_dR_r}, T_{CR_r})}{|UDR|} \qquad (2)$$

Results

We tested the effectiveness of our method on three datasets using leave one out methodology[4]. The number of interaction cycles taken by the system to achieve the target is used as the basis of comparison between various methods.

Query Size	MLT	MLT AS[5]	MLT TM [3]	**EBR**
1	11.41	6.90	6.28	**5.13**
3	9.54	5.89	5.45	**4.64**
5	6.42	4.04	3.94	**3.59**

Table 3: Efficiency in Camera dataset (the lesser the average cycle length the better)

Query Size	MLT	MLT AS	MLT TM	**EBR**
1	24.42	14.32	12.14	**9.28**
3	19.18	10.91	9.64	**7.55**
5	15.12	8.08	7.53	**5.85**

Table 4: Efficiency in Car dataset (the lesser the average cycle length the better)

Query Size	MLT	MLT AS	MLT TM	**EBR**
1	8.29	6.09	5.50	**4.08**
3	6.14	4.22	3.96	**3.20**
5	3.67	2.19	2.19	**1.97**

Table 5: Efficiency in PC dataset (the lesser the average cycle length the better)

MLT: More Like This; MLT AS: MLT with Adaptive Selection; MLT TM: MLT with Trade-off Matching; EBR: Evidence-Based Recommendation

Conclusion

In this work, we have tried to derive inspiration from the human behaviour of looking for evidence in the process of conversation in CCBR by making maximal use of the limited feedback provided by the user. Empirical results show statistically significant improvements over existing methods.

References

[1] https://dictionary.cambridge.org/dictionary/english/evidence
[2] https://dzone.com/articles/what-is-evidence-for-a-recommender-system
[3] Sekar, Anbarasu, Devi Ganesan, and Sutanu Chakraborti. "Why Did Naethan Pick Android over Apple? Exploiting Trade-offs in Learning User Preferences." In International Conference on Case-Based Reasoning, pp. 354-368. Springer, Cham, 2018.
[4] Mc Ginty, Lorraine, and Barry Smyth. "Evaluating preference-based feedback in recommender systems." In Irish Conference on Artificial Intelligence and Cognitive Science, pp. 209-214. Springer, Berlin, Heidelberg, 2002.
[5] McGinty, Lorraine, and Barry Smyth. "On the role of diversity in conversational recommender systems." In International Conference on Case-Based Reasoning, pp. 276-290. Springer, Berlin, Heidelberg, 2003.

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