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Dimensions of Personalization and their effect on the Knowledge Containers in a CBR System

Mehmet H. Göker

Kaidara Software
330 Distel Circle, Suite 150, Los Altos, CA 94022
mgoker@kaidara.com

1. Dimensions of Personalization

The ever-growing amount of accessible data makes intelligent information search and selection without computational aid a hopeless venture. Personalization becomes an ever more desirable feature for IT systems. A computer system should ultimately be sophisticated enough to take individual variations in preferences, goals, and backgrounds into account and generate, select, and present personalized information. The goal of personalization is to make the interaction with a system subjectively more effective and efficient. Personalized systems obtain user preferences trough interactions with users, summarize these preferences in a user model and utilize this model to adapt themselves to generate customized information or behavior.

Personal preferences can have an effect on the *data processing level*, the *information filtering level*, and *the interaction and information presentation level* of a system. On the data processing level, the algorithms used on a data set to generate new information can be varied in accordance with the user's preferences. During information filtering, the results of the data processing algorithms can be screened based on the preferences of the user and subjectively irrelevant choices can be eliminated. The presentation of the information as well as the interaction with the user is also subject to personal preferences and needs.

Typically, a personalized CBR system will adapt itself by modifying the way it selects suitable items from the set of previously generated information in the case base, i.e. on the information filtering level.

In order to retrieve personalized solutions with a CBR system, it is necessary to acquire and model the preferences of the users along several dimensions. A user may have preferences with respect to:

- specific *items* (information entities),
- the relative importance of an *attribute* used in describing these items,
- *values* for an attribute of the items,
- the *combination* of certain attribute-value pairs, and
- the *diversity* of the suggested items and values.

Item preferences manifest themselves in the user having a bias for or against a certain item, independent of its characteristics (*item preferences*). The preferences regarding an attribute represent the relative importance a user places on the attribute while selecting an item (i.e. how important is cuisine vs. price: *attribute preferences*). Preferred values show the user's bias towards certain types of items (e.g. Italian restaurants vs. French restaurants: *value preferences*) whereas preferences for certain property combinations represent certain constraints with respect to the combined occurrence of characteristics in an item (accepts Mexican restaurants only if they are cheap: *combination preferences*). While the item preferences are related to single items, the attribute, value, and combination preferences are applicable to the retrieval process in general and the *diversification preferences* model the suitability of an item or value at a given time (Göker & Thompson, 2000).

2. Effects of User Preferences on the Knowledge Containers

Personalization along the dimensions mentioned above will modify the behavior of a structural CBR system by adapting the knowledge containers (Richter 1995). The following table lists some possible interactions for both positive and negative feedback regarding each dimension. The table is not meant to be exhaustive and can be expanded.

Kn. Cont: ***Preference***	***Vocabulary***	***Similarity Metric***	***Adaptation Knowledge***	***Case Base***
Attribute	Potential removal if not of interest.	Update of weighting factor(s).	Modify effect on adaptation in multi-attribute adaptation rules.	Indexing strategy can be adapted.
Value	Potential removal if not of interest.	Update of similarity metric.	Default value can be set. Adaptation rules can be updated.	Default value can be set.
Item	Values that are unique to this item can be removed.	Exceptions in similarity metric.	Default to equivalent but preferable item.	Potential removal from case base.
Combi-nation	Attributes may need to be combined.	Multi-attribute similarity metric.	Rules for cross-attribute Query completion and case adaptation can be learned.	Indexing strategy can be revised.
Diversifi-cation	Time-depen-dent query and case represen-tation.	Time-dependent similarity metric.	Time dependent adaptation rules can be learned.	Clusters of cases can be build to suggest 'equivalent alternatives'.

Table 1: Effects of Personalization on the Knowledge Containers

Since the concept of a container includes the possibility of moving knowledge from one container to the other without changing the total amount of information (at a given time), it is obvious that these effects will influence each other and can potentially be implemented in one container rather than the other.

3. Future Work: Personalization as Maintenance of a CBR System

If we define the goal of CBR system maintenance to be the preservation, restoration, or enhancement of system performance in a given context, we can claim that personalization can be viewed as CBR system maintenance in the context of a specific user and at a given time. Personalization will ensure that the performance of the system does not degrade and potentially is enhanced. The comparison of CBR systems that were initially identical but have been personalized for different users could also provide means to automate some of the rather difficult decisions required in CBR system maintenance.

4. References

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