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# An Experimental Analysis of the Behaviour of a Personalized Case-based Recommendation Strategy for the Learning Domain

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**Abstract:** This paper describes an approach that fosters a strong personalized case-based recommendation strategy of learning objects and analyses its behaviour on two dimensions: the pedagogical utility of the learning objects and the similarity with the student query.

**Keywords:** Case-based Recommendation Techniques, Personalization, Learning Objects.

## 1. Introduction

Recommendation technologies help to provide users with a personalized selection of information based on their preferences and needs. They have been recently applied to the learning field [2], where the ability of getting high-personalized recommendations is essential. The goal of our work on recommendation technologies in e-learning is to provide support for personalized access to the Learning Objects (LOs) that exist in educational repositories: a student poses a query about the learning concepts that she wants to practice during the current learning session, and the recommendation approach suggests the LOs that fits the student's long-term learning goals without significantly compromising her in-session interests represented in the query [3].

Our strong personalization model requires the existence of suitable learning paths over the different domain concepts and information about the student cognitive state in the form of persistent profiles. The learning domain concepts are represented using an ontology, which is populated with the concepts in the field of study. Ontologies provide taxonomical information that helps us to infer similarities between different concepts. On the other hand, a precedence property among the concepts reflects a suitable sequence of concepts during the learning process. Each LO has information about the learning concepts in the field of study that it covers. The student profile stores information about the goals achieved in her learning process and the explored LOs, which represent the student navigation history.

Our case-based strategy runs in two steps: retrieval and ranking. The retrieval stage looks for LOs that satisfy, in an approximate way, the student's short-term learning goals represented in a query and, using the learning paths in the ontology, rejects those LOs covering concepts that the current student can not study yet. Afterwards, the ranking stage sorts the LOs according to a quality value computed for each of them. The quality of a given LO $L$ for a student $S$ who poses a query $Q$ is computed using a quality metric defined as the weighted sum up of two terms: the similarity (*Sim*) between $Q$ and the concepts that $L$ covers, and the pedagogical utility (*PU*) of $L$ with respect to the student $S$:

$$Quality(L,S,Q) = \alpha \cdot Sim(L,Q) + (1-\alpha) \cdot PU(L,S) \quad where\ \alpha \in [0,1] \tag{1}$$

## 2. Experimental Analysis of the Recommendation Strategy Behaviour

For the experimental analysis presented in this paper, we decided to compute the similarity *Sim(L,Q)* between the concepts gathered in the query *Q* and the concepts that *L* covers assuming a simplification that consists on comparing the concept that results as the conjunction of the query concepts (*Q_conj_concept*) and the concept that results as the conjunction of the concepts covered by *L* (*L_conj_concept*). Then we can compute the similarity using a metric that we previously defined and successfully used in the past:

$$Sim(L,Q) = \frac{\left|super(Q\_conj\_c) \bigcap super(L\_conj\_c)\right|}{\sqrt{\left|super(Q\_conj\_c)\right|} \cdot \sqrt{\left|super(L\_conj\_c)\right|}} \tag{2}$$

where *super(Q_conj_c)* and *super(L_conj_c)* represent the set of all the concepts contained in the ontology that are superconcepts of *Q_conj_c* and *L_conj_c*, respectively. *Sim(L, Q)* values lie in [0, 1].

As far as the pedagogical utility *PU* value for a LO *L* and a student *S* is concerned, we have defined a metric that assigns high utility values to *L* if it covers concepts in which the student has shown a low competence level:

$$PU(L,S) = 1 - AM(L,S) \tag{3}$$

where *AM(L, S)* is the arithmetic mean of the competence levels that the student *S* has shown in the concepts that *L* covers

The analysis of the expected behaviour of our recommender system consists of the study of the ranked lists of recommended resources in two dimensions: the adaptation to the student long-term learning goals (her current knowledge state) and the satisfaction of her short-term interests. The pedagogical utility of a LO measures how useful a LO is for enhancing the student learning according to her current knowledge. Similarity with the query can be associated to the student satisfaction because the query represents the concepts that the student wants to learn during the current learning session. Due to the importance of short recommendation lists, we consider crucial that the most relevant LOs appear in the upper positions of the recommendation. The Normalized Discounted Cumulative Gain (NDCG) [1] measures the usefulness of a result list based on the relevance and the position of the retrieved documents and it compares the obtained gain with the ideal one. For experimental purpose, we have modified the *NDCG* metric in order to analyse the ranked recommendation lists of LOs with respect to their utility for the student ($NDCG_{PU}$) and their similarity with the query ($NDCG_{Sim}$). We compute these figures for lists of size *k* using the following equations:

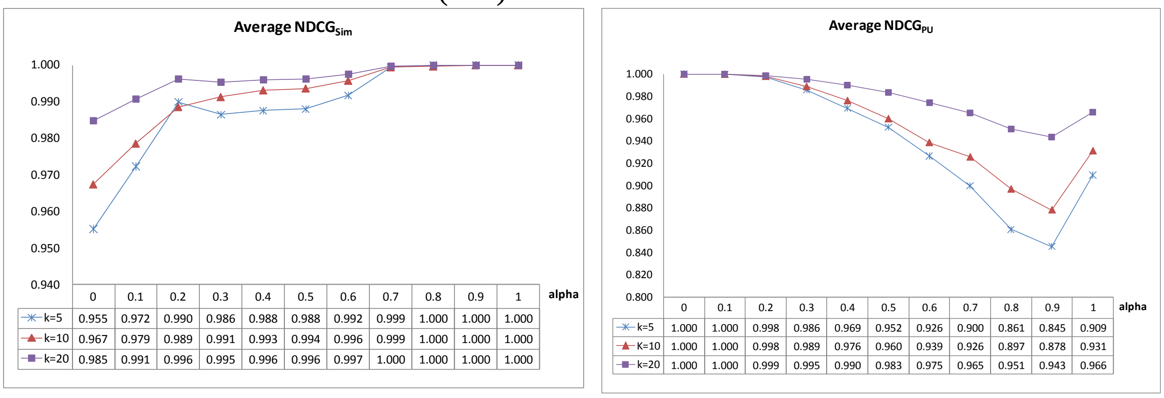
$$NDCG_{PU}(k) = \frac{DCG_{PU}(k)}{IDCG_{PU}(k)} = \frac{PU(L_1) + \sum_{i=2}^{k} \frac{PU(L_i)}{\log_2 i}}{IDCG_{PU}(k)} \qquad NDCG_{Sim}(k) = \frac{DCG_{Sim}(k)}{IDCG_{Sim}(k)} = \frac{Sim(L_1,Q) + \sum_{i=2}^{k} \frac{Sim(L_i,Q)}{\log_2 i}}{IDCG_{Sim}(k)} \tag{4}$$

where $IDCG_{PU}(k)$ and $IDCG_{Sim}(k)$ are the *DCG* values of the lists sorted by *PU(L)* and *Sim(Q,L)*, respectively.

We conducted an experiment to explore the impact of the Quality metric values in (1) in the properties of the recommended lists. We have also studied the behaviour of the approach with recommendation lists of different sizes. We have used a LO dataset with 549 LOs for learning Computer Programming. We have modelled a synthetic set of 30 heterogeneous student profiles that represent students who have explored approximately the 80% of the learning path in the ontology. We have performed 540 different recommendations with different values of $\alpha$ –ranging from 0 to 1 in intervals of 0.1— and list size *k* –5, 10 and 20 items per recommendation. The *NDCG* over all recommended lists was averaged to yield a single quantitative metric for each pair of α and *k* values.

## 3. Experiment results

Figure 1 summarizes the results using the proposed metrics, grouped by the size of the recommended list and plotted against $\alpha$. The tendency of $NDCG_{Sim}$ (Figure 1 left) does not differ significantly depending on $\alpha$ and on the list size. As far as the tendency of $NDCG_{PU}$ (Figure 1 right) is concerned, it differs depending on $\alpha$ and on the size of the list. However, any of the results obtained remains in high values of $NDCG_{PU}$ (the lower value obtained, for $k$= 5 and $\alpha$= 0.9, is 0.845). In general, we can stress that the case-based strategy obtains high values for *PU*, so the strategy proposes recommendations that satisfy the long-term learning goals. Additionally, we can see that the recommendation strategy always ensures that the proposed LOs meet the short-term goals, because a high similarity with the query is guaranteed. The recommendation strategy achieves high results in both *PU* and *Sim* even with small recommendation sizes (*k*=5).




| | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| k=5 | 0.955 | 0.972 | 0.990 | 0.986 | 0.988 | 0.988 | 0.992 | 0.999 | 1.000 | 1.000 | 1.000 |
| k=10 | 0.967 | 0.979 | 0.989 | 0.991 | 0.993 | 0.994 | 0.996 | 0.999 | 1.000 | 1.000 | 1.000 |
| k=20 | 0.985 | 0.991 | 0.996 | 0.995 | 0.996 | 0.996 | 0.997 | 1.000 | 1.000 | 1.000 | 1.000 |

| | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| k=5 | 1.000 | 1.000 | 0.998 | 0.986 | 0.969 | 0.952 | 0.926 | 0.900 | 0.861 | 0.845 | 0.909 |
| K=10 | 1.000 | 1.000 | 0.998 | 0.989 | 0.976 | 0.960 | 0.939 | 0.926 | 0.897 | 0.878 | 0.931 |
| k=20 | 1.000 | 1.000 | 0.999 | 0.995 | 0.990 | 0.983 | 0.975 | 0.965 | 0.951 | 0.943 | 0.966 |

Fig. 1 Comparison of $NDCG_{Sim}$ (left) and $NDCG_{PU}$ (right) against α in Equation 1 and *k*

## 4. Future Work

We plan to extend this analysis by using other similarity metrics that profit from hierarchical indexing contexts like the one used here. The use of other parameterized quality metrics will be also considered. This way we will observe the impact of these changes in the recommendation results and select those instantiations of the recommendation strategy that lead to better results for the two dimensions considered.

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