A Recommendation Cascade for e-learning

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Abstract

This paper is concerned with the presentation of a collaborative recommendation system that implements a cascade of strategies in order to support the learning process. Similarities between learners are determined by taking advantage of the underlying implicit or explicit personalisation and of the non-personalised modes of interaction. In the personalised approach implicit profiles are based on the patterns of behaviour of learners, while explicit profiles are generated from the results of a questionnaire on learning style. The non-personalisation approach relies on the cumulative intervention of a community of learners implied by the recorded frequency of the usage of objects by learners, and by the expert rating of objects by teachers. Content-based and collaborative approaches are combined into a hybrid model that widens the range of objects to which a learner may be exposed. The quality of service of the recommendation system is evaluated by considering the accuracy of its predictive capability on a publicly available data set.

Keywords: *recommendation, personalisation, explicit profile, implicit profile, neighbourhood*

1. Introduction

The availability of vast amount of educational material on the Web has given rise to concerns over access to relevant content by learners [1]. Although the deployment of an increasing number of repositories has provided more focus, the onus is still on the learner to navigate successfully the information structures to find relevant material. In e-learning systems, in particular, the provision of suitable material to individual learners presents a significant challenge. Adaptive e-learning systems have emerged in response to the inadequacy of the provision of undifferentiated learning content [2]. This shift from passive sources of information to more assistive systems requires the identification of the profiles of the user and the effective satisfaction of their needs.

With the advent of e-learning technologies it has become easier to achieve two of the most important objectives of instruction design: the provision of adequate guidance and the fostering of student-centered learning. This is usually facilitated by mediation systems whose aim is to satisfy the stated or implied needs of the learner through the selection and presentation of appropriate learning objects. Various perspectives are brought together by the mediation process: user profiling, learning object (LO) representation and provision of appropriate LOs. The interaction between learners, which may be indirect and may involve interaction with the same object by different learners, is often seen as an important collaborative facet of the learning process. Despite the arbitrary, asynchronous and independent intervention of individual learners, a collaborative map of learners can be derived explicitly from stated interests or inferred implicitly from observed common behaviour.

The aim of this paper is to present a collaborative recommendation system that implements a cascade of strategies in order to support the learning in an e-learning environment. The collaborative process determines similarities between learners by taking advantage of the underlying implicit or explicit personalisation and of the non-personalised modes of interaction [3]. In the personalised approach implicit profiles are based on the patterns of behaviour of learners and their interaction with learning objects, while explicit profiles are generated from the results of a questionnaire on learning style. The non-personalisation approach draws upon the cumulative intervention of the community implied by the recorded frequency of the usage of objects by learners, and by the expert rating of objects by teachers. The integration of these strategies is motivated by the need to provide seamless support to learners and to address the issue of 'the cold start' in collaborative systems. Content-based

and collaborative approaches are combined into a hybrid model that offers a wider range of objects to learners. A publicly available data set is used for evaluating the accuracy and the predictive capability of the proposed recommendation system. The recommendation process is an integral part of a basic learning management system.

The contribution of this work lies in the integration of a set of collaborative-based strategies into a recommendation cascade and its enhancement with a content-based approach. The different perspectives that drive the filtering process are designed to provide a more accurate and comprehensive set of recommendations through the systematic application of the stages of the cascade. Unlike most published work, the proposed framework is marked by the depth of the recommendation cascade and the range of the techniques for building neighbourhoods.

The remainder of the paper is organised as follows. Section 2 provides an introduction to recommendation systems. Section 3 presents the proposed recommendation system. Section 4 gives an evaluation of the recommendation process. Section 5 puts the work in perspective and Section 6 concludes the paper.

2. Recommendation Systems

It is argued that the provision of recommendations leads to better goal achievement [4]. Personalisation through recommendation depends on whether the focus is on a single user or a community of users. In content-based systems, learning content is selected according to the preferences of the learner, which are expressed either explicitly or implicitly. Collaborative-based systems on the other hand rely on the similarity between the interests of users when retrieving relevant learning content.

A content–based approach is characterised by its emphasis on a detailed analysis of content, its usage and an explicit rating of items. Learning content is recommended according to the preferences of the users or the items they have previously selected [5]. Content-based systems are easier to implement and tend to be faster. One of their limitations is the restriction of users to items that are similar. For this reason content-based systems are often criticised for their lack of serendipity. Within a community of users however the selection of items is achieved by considering the behaviour or profile of a number of users.

A collaborative approach is content agnostic and exposes users to a variety of items. It puts more emphasis on user behaviour and on the determination of the correct neighbourhood. Collaborative filtering involves finding users that are similar such as those that are statistically close to one another, and grouping them into neighbourhoods or clusters. Each group is the recipient of specific set of recommendations [6]. In the construction of neighbourhoods, collaborative filtering suffers from some limitations. Items which have not been selected or rated cannot be recommended. Furthermore, in situations where a large number of items are held and only a few users are active, many items may not be selected. From the user perspective the system is unable to make recommendations in the absence of profiles or any recorded patterns of behaviour of new users. These limitations are different manifestations of the 'cold start' problem.

One way of addressing this issue is to widen the set of criteria by requiring users to rate items explicitly and by recommending the most popular items. The rating can subsequently be used to generate a collaborative profile, which will form the basis of a neighbourhood.

The limitations of the content-based and collaborative-based approaches have led to the introduction of hybrid systems. These systems tend to integrate the features of both approaches and to enhance their strengths while minimising the impact of their drawbacks. Fab is one of the earliest systems that attempted to integrate the advantages of the two methods without inheriting the disadvantages of neither [7]. A hybrid content-based collaborative system is often created by first using content analysis (implicit profile) to generate and maintain profiles.

The recommendation process involves three fundamental steps:
1. Identification of association between user and items
2. Determination of the neighbourhood
3. Recommendation of the top N most relevant items.

Recommendation systems are particularly relevant to a virtual classroom environment, where learners benefit from the experience of the community. It is often argued that recommendation systems offer many advantages in a learning environment [8]. Relevant material can be found easily and learners are better engaged with the learning material. At the heart of collaborative methods lies the assumption that learners have overlapping interests and that these common interests can be identified by using different perspectives. The learning process is seen as a potentially collaborative process. The participation of individuals in the acquisition of new skills through the interaction with common or shared learning material identifies implicitly a sphere of collaborative behaviour. Clustering around similar characteristics can enhance the learning experience through collaborative filtering [9].

3. A recommendation-based LMS

A learning management system (LMS) was designed and implemented to satisfy a number of objectives. It provides an integrated environment for learners, instructors and learning content and supports the:
1. Provision of personalised resource recommendations to learners as far as possible.
2. Submission of learning resources to the system by teachers or instructors.
3. Ability by teacher to monitor resource usage by learners
4. Assignment of learners to one or more groups/courses
5. Creation by teachers of courses and assignment of learners

The main requirement of the system is that it should provide relevant recommendations and that the recommendations are based on useful neighbourhoods. This implies that firstly, the issue of the 'cold start' must be addressed explicitly and secondly, that the neighbourhoods are generated according to relevant and meaningful criteria.

3.1. Architecture

The system was implemented as a Web-based application. The diagram in Figure 1 indicates how the recommendation generation draws upon the personalized and the non-personalised components. The functionality of the system is served by an extensive database and by a search engine. Figure 2 shows some of the functionality available to the teacher. The digital resources of interest in the system are Web pages identified by their URL, which are stored and manipulated.

3.2. Recommendation

The starting point of the recommendation process is the identification of an association between learners and content and the formation of a neighbourhood. Content usage patterns and content rating are the two main techniques that form the core of the recommendation system. The content usage involves recording implicitly content that learners have viewed or used, whereas the rating of content is performed explicitly by learners. This forms the basis of neighbourhood generation.

A neighbourhood cannot however be generated accurately if there is little or no information for determining the similarity between users. This applies to situations where a new learner has no page view history, where there is little difference between the pages viewed by learners in a neighbourhood and those
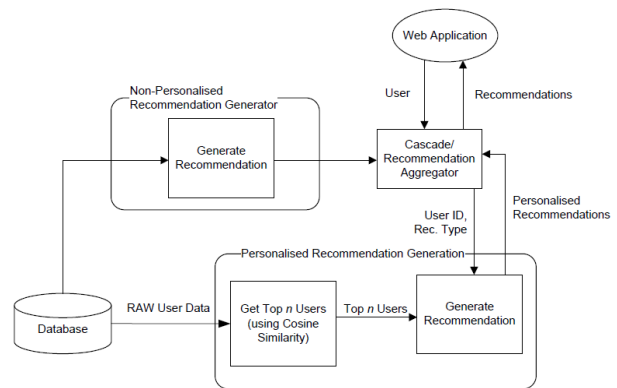

Figure 1. System Architecture

viewed by the active learner, and where there is a lack of data for any learner on a course. The recommendation capability of the system can be enhanced by including other techniques for generating neighbourhoods, such as the explicit rating of objects and the explicit determination of the learning style of learners. The rating of objects has become an extremely important component in the selection of objects. It is now considered an integral part of the metadata since it is used in the search of LOs in many repositories [10]. Many systems take the learning style as a basis for building adaptive e-learning systems [11]. In this system, the Felder and Silverman model [12] was chosen as proof of concept. Other models can easily be incorporated into the system. The evaluation of objects and their rating by teachers/instructors is significant in many ways. In addition to providing instructional guidance it can deal with the issue of bias and malicious behaviour [13]. All these strategies for building neighbourhoods are integrated into a cascade of recommendations in order to meet the requirements.
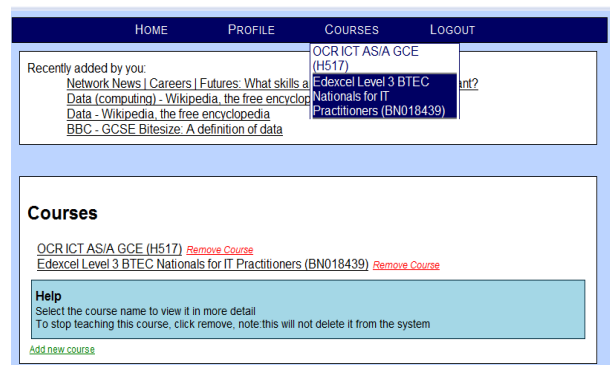

Figure 2. A teacher's view

Recommendation Cascade

The cascade is the result of an attempt to support the learning process from different perspectives. It

combines elements of evaluation of modes of interaction as well as feedback from teachers. The cascade is designed to allow for an exhaustive recommendation process, which involves the generation of a neighbourhood for each stage (Figure 3). It operates within a community-based environment and combines personalised and non- personalised recommendations. A hierarchy of neighbourhoods is identified with the top one having the highest semantic content. At each level, a neighbourhood is generated incrementally, sequentially and on demand, in order to address the limitations of the previous stage. This prevents duplications and preserves the order of the recommendations. The ultimate neighbourhood is the union set of all the previous ones. In the cascade the generation of each neighbourhood is triggered by a test, $n < R$, where R stands for the minimum number of recommendations required, and n represents the current number of generated recommendations. Non-
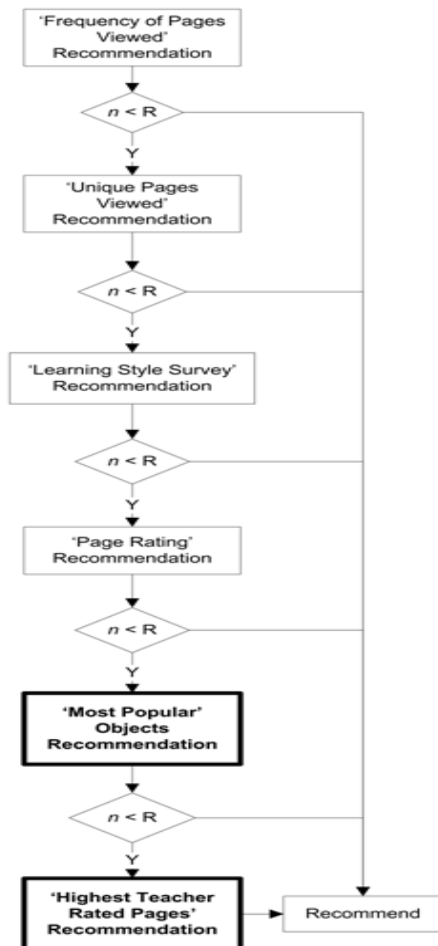

Figure 3. Recommendation cascade

personalised recommendations are distinguished by bold lines.

The personalised recommendation is achieved by implicit and explicit profiling. In the implicit approach a neighbourhood is generated by considering the pages that were viewed by learners. The first attempt to generate a tightly-coupled neighbourhood involves considering the frequency of viewed pages and is an integer-based comparison. If the number of recommendations is not sufficient a Boolean-based comparison, where pages are viewed or not-viewed is applied to generate a wider but relevant neighbourhood and thus enhance the quality of recommendations. If the implicit phase fails to generate enough recommendations a neighbourhood is generated explicitly by clustering learners according to learning style, and then, if required, by grouping them according to the 'rating' they assign to common learning objects.

If the level of personalised recommendation is unsatisfactory the cascade switches to the non-personalised mode of recommendation. The qualitative transition is marked by the absence of neighbourhood and the reliance on the judgment of the community of learners and in particular on the LOs with the highest rating. The last resort in the non-personalised mode in the cascade is provided by the expert rating of LOs by teachers/instructors.

Figure 4. Hybrid recommendation

Hybrid recommendation

Additional functionality includes the ability to provide suggestions of other pages, based on the page currently being viewed. There are two types of recommended pages, not already viewed by the learner (Figure 4): those that are similar to the viewed pages and those viewed exclusively by users in the same neighbourhood. The collaborative cascade is thus enhanced by content-based recommendation into hybrid recommendation. The suggestions based on content were facilitated by the search engine.

Cascade Configuration

Some control over the recommendation process was one of their key design issues. Feedback from instructors has shaped the structure of the system. The system allows potential instructors to set some parameters in order to suit environmental conditions. This covers the type of recommendations (Pageviews,

pageview, learning style, learner rating, popularity, and teacher rating), the size of neighbourhood and the number of recommendations.

3.3. Recommendation generation

Figure 5 gives an outline of the generation of recommendations based on neighbourhoods. It consists of a number of stages: data extraction and transformation, neighbourhood creation, retrieval of learner's data and recommendation generation.

Each neighbourhood is determined by applying a similarity rule. Two methods were implemented for determining the similarity between items, a statistical method, Pearson correlation, and a vector-based technique, the cosine rule. The following formula is used for the calculation of the correlation:

$$corr(A, U) = \frac{\sum_{i=1}^{n}(A_i - \bar{A})(U_i - \bar{U})}{\sqrt{\sum_{i=1}^{n}(A_i - \bar{A})^2}\sqrt{\sum_{i=1}^{n}(U_i - \bar{U})^2}}$$

$$R = (\square\, U\square_i 1 = (o_i 1, o_i 2, \dots, o_i \gamma$$
$$U_2 = (o_1, o_2, \dots, o_n),$$
$$\dots$$
$$U_n = (o_1, o_2, \dots, o_n)$$
$$)$$

R is a list of vectors, where each vector represents the data of one user, and each dimension represents the interaction with one object.

Representation Generator (Data Mapping)

R

Neighbourhood Generator

K (Key user vector), Ns (Neighbourhood Size)

$K = (o_1, o_2, \dots, o_n)$, the Key user vector, is a single vector where a dimension represents the same object interaction as in R .

It is important to note that $K \cap R = \emptyset$; i.e. the data representation must not contain K, as this will skew the

N , top n most similar user vectors and K,the Key user

$N \subseteq R$, N (Neighbourhood) is a subset of R (the initial dataset Representation)
$|N| \leq Ns$, N is less than or equal to Ns, the size of the neighbourhood

Recommendation Generator

Rs (Number of Recommendations)

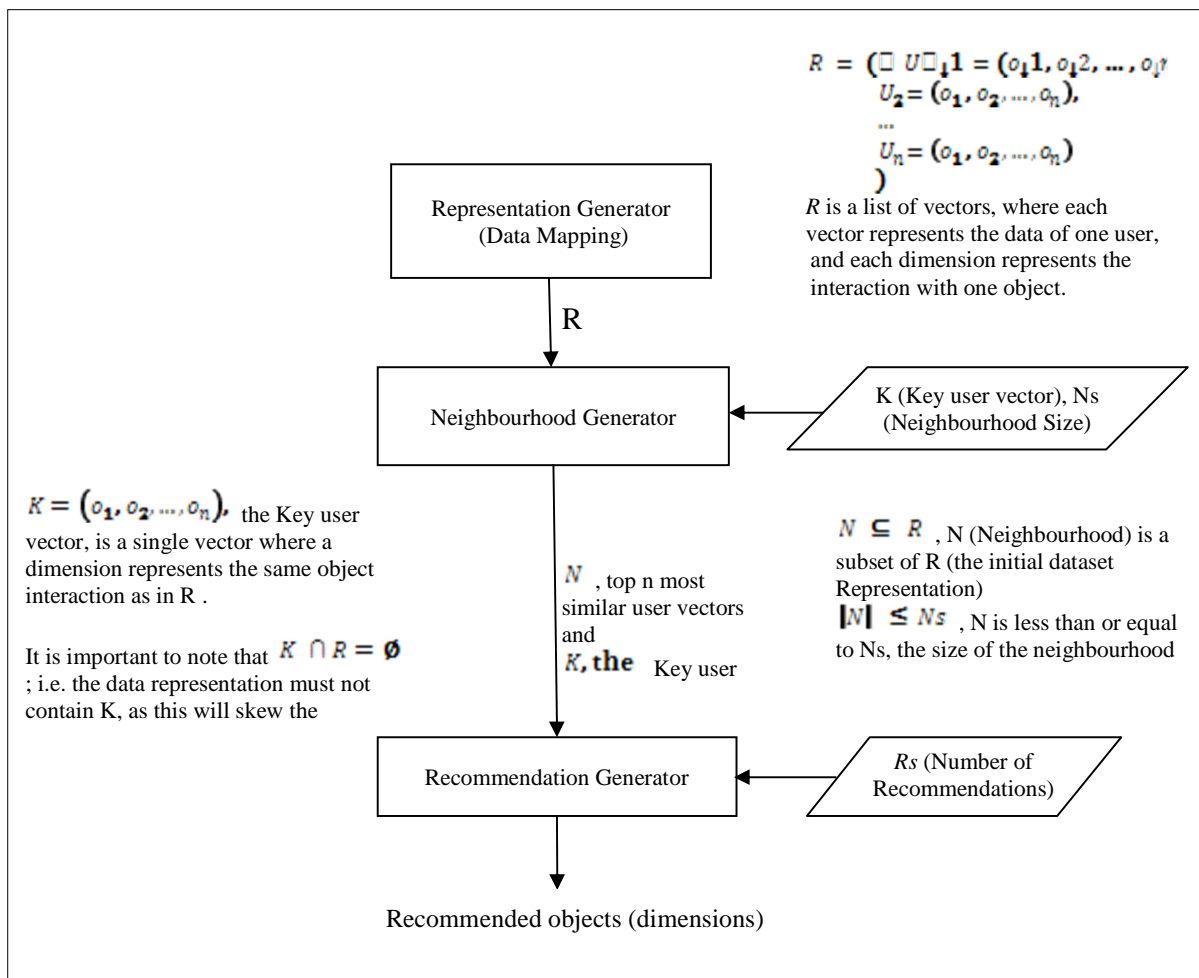Recommended objects (dimensions)

Figure 5. Recommendation generation

The cosine rule operates on two sets of data represented as vectors and calculates the cosine angle between them:

$$\text{similarity} = \cos(\theta) = \frac{A \cdot B}{\|A\|\|B\|} = \frac{\sum_{i=1}^{n} A_i \times B_i}{\sqrt{\sum_{i=1}^{n}(A_i)^2} \times \sqrt{\sum_{i=1}^{n}(B_i)^2}}$$

4. Evaluation

One widely held assumption is that the viability of a recommendation system depends on the quality of its predictive capability. This focus on process may provide an adequate evaluation of the recommendation system and of its applicability as a generic model to a recommender–generated data set. As this is an ongoing research project the system has not been populated with enough learning objects or learners to subject them to a statistical analysis. The experiments were therefore designed to provide an insight into the behaviour of the system, and more specifically into the impact of the size of the neighbourhood on the predictive capability of the algorithm. The experiments were conducted with the cosine rule and the Pearson correlation similarity measures.
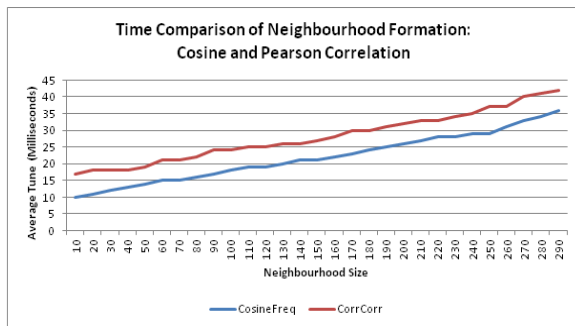

Figure 6. Performance

The sample data used for evaluation was taken from the MovieLens data set, which provides 100,000 ratings (1-5) from 943 users on 1682 movies dataset. The data set was downloaded from the Grouplens website [14]. The data set on user-object usage was split into **Tr**, the training set (80%), and **Ts**, the test set (20%), such that $Tr \cap Ts = \emptyset$. **Tr** stands for the 'current' data on users and corresponds to the algorithms 'representation'. **Ts** represents the 'future' use which was compared with the recommendations returned by the algorithm.

The size of the neighbourhood was varied between 10 and 300 in increments of ten, for each increment a recommendation of 5 items was generated for each user in the representation. The recommendations generated were then compared the 'future' dataset (test data), and values of relevance were determined.

4.1 Performance

The average time taken to produce a recommendation with each method was also used to assess its speed. In the generation of a neighbourhood the results indicate that the cosine method is nearly as accurate as Pearson correlation (Figure 6). The difference was so small that it can be considered as negligible. The cosine method is however faster by an average of 6.1 milliseconds.

The graph indicates that the time taken to make a recommendation increases with the size of the neighbourhood. Since all the stages of the cascade may be activated sequentially, the speed of the recommendation generation is a critical component in the provision of quality of service (QoS).

4.2 Precision and recall

One experiment was also devised to assess the quality of the recommendation. This was expressed in terms of precision and recall. Precision calculates the proportion of correct recommendations in the recommendation set. It measures how well the system performs in not making the wrong recommendations. Recall represents the proportion of correctly identified recommendations (Hit rate) in the maximum number of correct recommendations. It is a measure of the completeness of the recommendation process.

$$Precision = \frac{|hit\ set|}{|no\ of\ recommendations|} = \frac{|H|}{|R|}$$

$$Recall = \frac{|hit\ set|}{|test\ set|} = \frac{|H|}{|Ts|}$$

As there is usually an inverse relationship between precision and recall these two measures are often combined into a single value, the F1-measure:

$$F1 = \frac{2 \times recall \times precision}{recall + precision}$$

The training set was used to generate a recommendation and the test data was used to evaluate it. This involved the comparison of recommended items (**R**) with items that the user looked at a later date. This is done by calculating a hit set (**H**), which is the set of items occurring in the test set (**Ts**) and the recommended items, $R \cap Ts = H$. The average F1-measure is taken for all users in the data set to give a singular value assessing the quality of the recommendations made.

The analysis of the recommendation algorithm shows a very low F1-measure of on average 0.02 (Figure 7).

This may be the result of the mismatch between the cascade-based system and MovieLens recommendation system; this is evident in the difference in the dimensionality of the data and in the sparsity of the vectors. The mismatch may also be due to the fact that MovieLens relies on explicit rating only, whereas the proposed system gives precedence to implicit approaches. The explicit rating is only invoked as the fourth strategy. This low F1-measure confirms that the recommendation system is not generic, and may require specific data to operate properly.

Although the MovieLens data helped shed some light on the process, an enhanced evaluation of the recommendation system would involve the rating by learners of the quality of the recommendation objects in a populated learning management system.

5. Discussion

Many hybrid systems have been introduced in e-learning in order to enhance the learning process, by recommending relevant LOs to learners. In Khribi et al [15] the collaborative filtering method is applied first, followed by content-based filtering. This approach requires the specification of the model of the learner in terms of his knowledge, which is represented by a sequence of weighted visited learning objects. The cascade is made up of two stages, and only one collaborative method is considered. The 'cold start' issue is not addressed explicitly. The evaluation of the system is in terms of precision and recall.

Di Bitonto et al [16] proposed a recommendation cascade which combines a high priority ontology-based technique for retrieving objects related to topics of interest and a low-priority rule-based method based on the Index for Learning Style (ILS) [12]. This hybrid approach provides an implicit mechanism for addressing the 'cold start' problem.

In the Protus system [18], learners are initially clustered into groups by a combination of automatically generated learning style and an explicit method based on the Felder and Silverman model of

Figure 7. F1-measure

learning style. Data mining techniques are then applied to discover patterns of behaviour among learners. This approach promotes model-based methods, and is scalable. The learning style component provides a mechanism for dealing with 'the cold start' problem.

This brief overview of some recommendation systems has highlighted the range of methods that can be combined to retrieve relevant items. They all conform broadly to the content-based and collaborative-based combination. The proposed approach conforms to the hybrid model as well. It is characterised however by the depth of the collaborative component of the cascade, the prominence of implicitly generated neighbourhoods, and the way the 'cold start' is addressed explicitly.

Unlike many existing systems it is the collaborative-based approach that drives the recommendation process [15]. The content-based method is subordinate to the collaborative-based approach. A collaborative driven approach puts more emphasis on the different facets of the learning process.

The power of the collaborative approach lies in its capacity to transcend personalisation. Personalised collaborative behaviour can manifest itself in the explicit rating of LOs by learners, where a specific rating assigned by a group of learners can act as the signature of their neighbourhood. In contrast, an example of non-personalised collaborative behaviour can be based on the popularity of a LO without rating or on the high rating given by an instructor to a LO. These metrics are considered as indicators of the inherent quality of a LO irrespective of the preferences of the individual learners.

The proposed cascade represents the convergence of individual preferences, common behaviour and expert guidance. Through the generation of different neighbourhoods it subsumes implicitly aspects of the three forms of interaction identified by Moore [19]: learner-content, learner-learner and learner-teacher/instructor.

The vertical and incremental generation of neighbourhoods in the cascade is motivated by quality concerns. It is possible to opt for a quantitative approach and to widen the size of the neighbourhood by relaxing the criteria for its generation. This would involve, for example, opting in the first instance for a single page view and ignoring the overlap in multiple page views. This flattening of the cascade would however weaken the semantic content of the recommendations and reduce their relevance.

The scope for improving the recommendation process covers many issues. The implicit approach is supported by a limited set of criteria. The relevance of the recommendations can be enhanced by including criteria such as bookmarking. In addition, there might
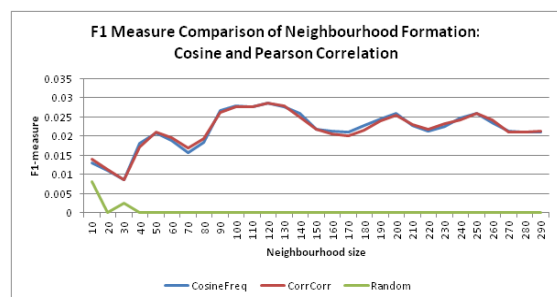
be some concern over the cognitive load that explicit profiling may put on learners. It is assumed however that by definition, learners play an active part in the learning process. This form of eliciting profile information is intermittent and common in educational environments. Another area for investigation concerns the impact of the different learning styles on the construction of the neighbourhoods.

The requirement that learners are subjected to a test to establish their learning style has a pedagogical rationale, and the evaluation and rating of LOs by learners and teachers can be very beneficial in an educational environment. The learning style can be the basis for adaptive learning paths, whereas the teacher intervention is designed to ensure quality of material and consistency. The evaluation was aimed at validating generically the predictive power of the system. A more refined evaluation of the value of the quality of the LOs would however shed more light on the role of each stage in the cascade.

6. Conclusion

The proposed hybrid approach has the merit of identifying LOs viewed in different neighbourhoods, and of widening the pool of objects that can be recommended. Moreover, it contributes to the selection of a wide range of LOs and exposes learners to new but related material, even if a LO has not been rated or accessed. The integration of different strategies into a cascade represents an eclectic mix of approaches and deals explicitly with the 'cold start' problem.

The recommendation system was deployed within an embryonic LMS where it incorporates a number of elements. Its fuller potential is better realised in a fully-fledged LMS, which is adequately populated. With different levels of personalisation and implicitness and with the combination of content-based and collaborative approaches to recommendation, the cascade is designed to provide educational guidance and encourage student-centered learning.

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