Towards Time-dependent Context-sensitive User Data for recommending Learning Objects

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INTRODUCTION

Recommendation engines quite often face a lack of metadata describing single users and whole communities, the offerings as well as the relation between a user and an offering. Furthermore, time-dependent contextualization plays a crucial role in predicting the user's behavior in various situations, how he will interact with the offered services and what items he will consume next. In a digital classroom, analysis of student's interactions with the learning media provide important information about user's behavior, which can lead to a better understanding and thus optimize teaching and learning. Over the period of a course, students tend to forget the lessons learnt in class. Learning predictions can be used to recommend learning objects users need most, as well as to give an overview of current knowledge and the learning level.

Content based filtering compares the need of a user for a specific learning objects with a set of learning objects. However, collaborative filtering uses the knowledge of behavior of similar users and their successful completion of learning objects, in recommending learning objects to the user. The knowledge level of a user towards these items is maintained in a two dimensional user-item matrix. The representation of a time based function in such a format is difficult, since the knowledge level of a user with a learning object changes continuously depending on various factors.

APPROACH

Learning recommendation is all about identifying the learning needs of a user *u* for an item *i*. The user-item-pair is presented by a relevance score having the value from 0 to 1, where 0 indicates the lowest relevance and 1 indicates the highest possible relevance. The relevance score defines a time and context dependent value, where context is represented by the several factors stated below. Thus, it is expressed as a time dependent function:

$$relevance_{score} = lb_{u\ i}(t)$$

The learning need (Lernbedarf) function $lb(t)$ is derived from several sub-functions $lb_x(t)$ of individual factors $x_1 \ldots x_n$, as a function of time, for data that were collected from learning process or derived from the course structure. This data can be abstracted as linear and/or simple functions in small intervals. The different factors considered are:

- Retrieval/processing time of a learning object.
- Self-assessments for this learning object.
- Performance in exercises.
- The time in which the lectures are held for this learning object in class.
- Exam relevance if applicable.
- Forgetting effect of gained knowledge.
- Averaged learning needs of other users.
- Fulfilled pre-requisites of the learning object.

Each factor's relevance score represents an aspect of the learning need – e.g. percent of questions wrongly answered by the user. All single-factor functions are weighted. The weighted average of all factors describes the total learning need of the learning object for that user. Figure 1 shows the curves for different factors with respect to time and also the weighted average of all factors, which describe the learning need for a specific item. The weighted function is calculated as

$$lb(\mathrm{t}) = \frac{\sum_{x=0}^{n} \mathrm{w}_x * lb_x(t)}{\sum_{x=0}^{n} \mathrm{w}_x}$$

Here *t* is the current time, w_x is the weight of a single factor and *n* is the number of factors. The weights are predefined by experts, such as teachers.

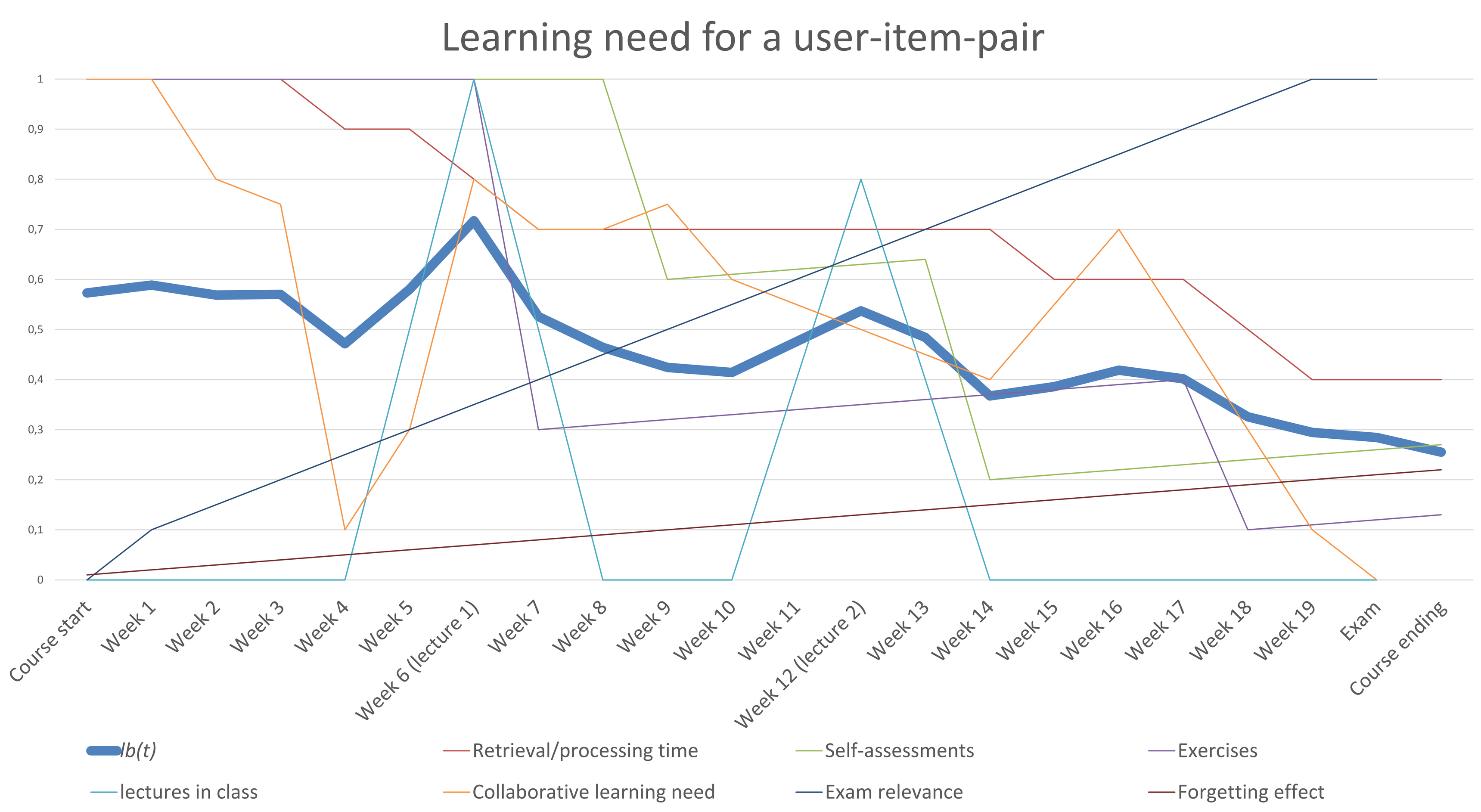

Figure 1: Example of a learning needs function with individual factors

ADVANTAGES

- **Time-dependent context-sensitive representation**: The learning needs of a user greatly vary over time and depends on many factors. Current content based and collaborative filtering approaches rarely consider this aspect.
- **Prediction Capability**: Based on actual and predictable value pairs of individual factors, the future course of the resulting overall function can be determined.
- **Hybrid Filtering**: This method combines both content based and collaborative filtering methods. The strengths of these approaches can possibly be expanded for time based approach.
- **Performance**: The model of the recommendation engine can be created offline. A 3-dimensional matrix with time factor used instead of 2-dimensional user-item matrix. Therefore a function for each user-item tuple can be created.
- **The personal knowledge level** defines how successful is a student in learning a learning object and is inversely proportional to the learning need of the student towards the learning object. Knowledge level $kl(t)$ can be computed from learning need $lb(t)$ as $kl(t) = 1 - lb(t)$.
- **Visualization**: The need for items as well as the knowledge level can be visualized for the end user.

RELATED WORK

A novel research study conducted by Worcester Polytechnic Institute [1] aims at enhancing long term retention of learnt knowledge, by creating a Personalized Adaptive Scheduling System for retention tests. In order to improve the online learning environment, Hayriye Tugba Ozturk [2] proposes a method of sequential analysis of discussions among students and teachers in Learning Management System (LMS). A similar kind of research is carried out by Ángel F. Agudo-Peregrina [3], where the interactions in the LMS is analyzed based on an agent (student-student, student-teacher, student-content), frequency of use (access to learning resources, creation of class interactions and so on) and participation mode (active & passive) for predicting student's academic performance.

More research on time-dependent recommendation engines have been done in the area of movie predictions: A Time-Context based Collaborative Filtering algorithm [4] proposed by Liang He describes the inclusion of rating time in the computation of predictions for movie ratings. A similar approach of including the rating time was proposed by Pooyan Adibi [5] for finding the users' interests towards group of items and using that for prediction of movies. Finding neighborhood of the user with a time-based K-nearest neighbor algorithm [6] was proposed by Yue Liu in which they make use of torrent download time for calculating the recommendation.

In contrast to the above mentioned papers, this approach processes continuous time-dependent user data and describes a way to integrate different context factors, which are computed by different mathematical functions. Also, it is a more generic approach, which can be used in different areas.

CONCLUSION

Time context is a very important aspect of context-sensitive recommendation system. We can derive valuable information from the system and better visualize learning needs at different points in time, by considering the time aspect. Time-dependent mathematical functions can be reused for computation with different factors. This approach can also be applied in different application areas like recommendation of movies, items and so on, apart from learning recommendation.

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