# A Refined Case-Based Reasoning Approach to Academic Capacity Planning

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**Abstract.** Academic capacity planning is a knowledge-intensive process that has to be based upon predicted course demand. Planners have to take into account students' current course achievements, prospective future course selections, time constraints as well as a wide range of different rules for graduation. The research project proposes a refined case-based reasoning (CBR) approach for anticipating students' future course selection as a means of long-term demand forecasting. The case-base is dynamically interpreted with regard to stored cases' problem descriptions and solutions. Moreover the structure of cases is heterogeneous depending on the students' course achievements. The retain phase of the traditional case-based reasoning cycle is replaced by an adjustment phase that ensures retaining up-to-date, real-world cases only. The results of the case-based reasoning processes are aggregated to support capacity planning.

Keywords: Case-Based Reasoning, Academic Capacity Planning, Higher Education. Prediction

#### 1 Introduction

The German Higher Education Area has currently undergone dramatic changes. Institutions are intensively competing with each other for enrollments, complexity of curricula is steadily increasing and monetary and non-monetary resources are scarce [1, 2]. As a consequence of competition universities have to offer a demand-oriented portfolio of advising/support services and education. With regard to scarce resources it is indispensable to ensure and increase efficiency and effectiveness within institutions especially in the core process of teaching. In summary universities and their stakeholders find themselves in an environment that resembles that of private businesses with international competition [3]. As a means of efficient and effective resource management private businesses employ the method of capacity planning [4]. This requires knowledge of current or predicted demand figures. As a consequence of students' individual choices e.g. selection of majors, postponing enrollment for courses and the increasing complexity of curricula, demand figures tend to be fraught with high uncertainty within the academic environment. Therefore the application of capacity planning proves difficult and there is a lack of actual use.

## 2 Objectives

The research project proposes a refined CBR approach for rolling prediction of future course enrollments which serve as a demand-figure for academic capacity planning. Following requirements are to be met:

- students' individual choices have to be considered,
- the method has to lead to valuable long-term predictions in increasingly complex academic environments (scalability),
- maintenance effort should be low especially in terms of adaptability to curricula changes and graduation requirements.

#### 3 Related Work

Literature provides several concepts for supporting academic planners with predicted demand figures. Largely, researchers propose model-driven decision support systems relying on network simulation models [5], Markovian analyses [6, 7] or failure rate-based mathematical models [8]. None of the proposed models considers students' individual choices, most of them are static in nature lacking the possibility of adaptation to changing environments, and focus on short-term planning (e.g. one term ahead) only. Attempting to apply these models to increasingly complex and rapidly changing curricula for long-term demand prediction would lead to a prohibitory increase in the models' complexity.

CBR is an approach that solves new problems by remembering similar previous situations and reusing knowledge and information of that situation [9]. It is especially useful in unstructured domains in which causal models do not exist or are hard to find [10]. In the academic domain CBR applications have mainly been deployed to support academic advising by predicting student class performance based on a student's current performance and the performance of preceding students in the same class [11] or for recommending courses to students for one following quarter [12]. These applications are rather narrow in scope and focus on single students only. Nevertheless they demonstrate that student behavior can be anticipated by CBR.

# 4 Research Methodology

The research methodology is based on the design science approach [13, 14] which is particularly applicable to problems with well-defined requirements but lacking a satisfactory solution as it is the case with predicting demand figures as a basis for academic capacity planning (need). A prototype deploying a refined CBR methodology for demand forecasting will be constructed (artifact) and tested with real student data for different study programs (evaluation).

# 5 Proposed Solution

In order to support the knowledge-intensive process of academic capacity planning individually composed schedules of study are predicted. Each student is considered as one case represented by personal features (e.g. age, sex) and the student's course history. The course history is implemented as a set of features representing all attended courses ordered in the sequence of attendance. At the instant of time t (the moment the prediction process starts) the case-base therefore consists of cases that are heterogeneous: All personal features will be assigned with values whereas the amount of features representing the course history will differ between cases depending on the individual progress of each student. Besides being part of the case-base all cases representing students not meeting graduation requirements in t are considered as unsolved cases, too. The first three steps of traditional CBR (retrieve, reuse, revise) are executed for all unsolved cases. In the course of this the case-base is dynamically interpreted: Depending on the realized course history of an unsolved case (e.g. all courses of semesters one and two finished) the corresponding part of the course histories of all other cases in the case-base (features representing courses of semester one and two) together with the personal features are interpreted as case description. The remaining part of each retrieved and reused case's course history (semester three plus all courses attended until t) is interpreted as solution representing the predicted future course selection of the unsolved case. Future research will show whether to base retrieval either solely on the similarity between case descriptions or on algorithms taking into account e.g. a case's successfulness in previous predictions. The solution for every unsolved case is stored in an external database which finally contains the predicted course selections of all previously unsolved cases. These can then be aggregated in order to supply capacity planning with a prediction of course enrollment figures (see figure 1).

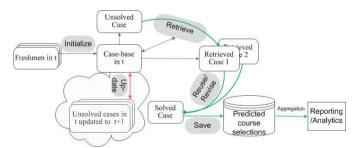


Fig. 1. Prediction Process

The last step of the traditional CBR cycle (retain) is replaced by a so-called adjustment phase. Each time a prediction is to be made, e.g. each term, the case-base is updated with new cases for all freshmen (only personal features). Additionally all cases that were unsolved in t have to be identified and updated with the students' achievements in the period between t and the new prediction time t+1. Thus the case-

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<sup>&</sup>lt;sup>1</sup> Concerning the term "knowledge" this paper follows the view of [15].

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base consists of up-to-date, real-world cases only. In case of curricular changes or varying graduation requirements the case base has to be adapted. Several alternative ways of adaptation will be considered e.g. removing cases violating rules imposed by new curricula, replacing case features with equivalent elements of new curricula or integrating a rule-based-reasoning module.

The described approach will prototypically be implemented for different study programs of the University of Osnabrueck in order to evaluate it against real student data and capacity planning efforts by human experts. For this purpose a catalogue of evaluation criteria will be set up.

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