Computational Intelligence for Communication and Cooperation Guidance in Adaptive E-Learning Systems

Mirjam Köck
Institute for Information Processing and Microprocessor Technology
Johannes Kepler University Linz
A-4040, Linz, Austria
koeck@fim.uni-linz.ac.at

Abstract

Adaptivity has become a prominent research topic during the past decades. There is a variety of application areas where adaptation can add benefit to systems, reaching from shopping portals to e-learning platforms. Despite the large body of work, Computational Intelligence (CI) techniques have been under-explored and therefore also under-exploited within the area of user-adaptive systems. This paper discusses the potential of employing CI approaches for the implementation of adaptivity within e-learning systems. Furthermore, it identifies scenarios where these techniques can improve the performance of an adaptive component. Specific focus is placed on the provision of guidance in e-learning systems, in particular with respect to communication/cooperation (as opposed to traditional focus on guiding learners through learning materials).

1 Introduction

Recent years have seen the importance of adaptivity grow within web-based systems in general and the field of e-learning in particular. Yet, the approaches of implementing adaptivity have not evolved much. Often adaptive behaviour is achieved by comparatively simple means, e.g. rule bases. Although such approaches evidently suffice for a wide spectrum of adaptive behaviours, they fall short in situations where it would be reasonable for the the system to acquire new knowledge or identify patterns at run-time.

The basic idea of this piece of work is to introduce approaches for implementing specific kinds of adaptation using CI (comprising various kinds of numerical information processing/representation) techniques and technologies. The premise of this proposition is that such technologies offer opportunities for a larger and more fine-grained spectrum of modeling and adaptation steps.

The discussion will focus on guidance, which is an important topic within adaptive systems. The term guidance is used here to refer not only to providing individualized help in finding a path through materials, but also, more importantly, to facilitating communication/cooperation among users. Possible incarnations of the later type include suggesting partners based on the rating of users' knowledge, predicting users' readiness and willingness to participate in activities, observing communication habits, etc. CI can arguably help to improve a system's performance in these areas and also increase the benefit of adaptivity in general.

2 Communication and Cooperation in Adaptive Systems

Communication and cooperation facilities are essential for almost every multiuser platform and reach from simple tools like a blackboard to more elaborate ones like shared document management. The synchronous form of cooperation is often termed "collaboration" and enables joint work via realtime cooperation facilities such as videoconferencing or desktop sharing. Communication incorporates both synchronous and asynchronous communication. Cooperation presumes communication but also includes more advanced means for concurrent (or at least joint) activity.

We refer to facilities such as chat, forum, blackboard, and private messages as communication tools and to shared notes, shared documents, group-based tasks or assignments as cooperation tools. In adaptive systems, user activities via such facilities are monitored and used as part of the input that goes into building up the users' models. User activities can reveal a lot of information about an individual's communication/cooperation habits and preferences. In turn, the system can use that information to characterize and classify users with respect to their cooperation-oriented characteristics. Moreover, the system can draw conclusions based on the correlation between a user's communication/cooperation activities with learning performance and activity.

Adaptive e-learning systems mostly provide guidance, e.g. to help a user find a learning path fitting individual needs, knowledge and aims. In fact, guidance can be used in more ways as it actually is the case in most systems. It can also be applied to communication/cooperation ([Soller, 2007], [Brusilovsky and Peylo, 2003]). Our approach differs from most of what is found in existing systems in various ways. First, we do not focus on resources but on activities. Second, we do not operate on a closed space (e.g. set of learning materials), but an open "space" of activities. For cooperation guidance, also the definition of success differs from the one we are used to. When guiding learners through materials, the aim is e.g. to ensure that they see all relevant resources, whereas when guiding activities we try to identify what leads to effective cooperation.

3 Adaptation Steps

This part describes forms of adaptation for communication/cooperation that could be achieved using "intelligent" approaches. The issues mentioned were chosen as descriptive examples – there is a variety of matters where adaptation can be improved with the help of the same techniques. A main part of adaptive behaviour is based on *prediction*. Within the scope of e-learning it includes predicting a student's performance in tests, preferred learning paths, and the readiness to participate in communicational activities. In order to draw assumptions, the system must be fed with user information, which is done by observing user/system and user/user interaction. Being able to infer knowledge and predict activity, the system can offer adaptation within the communication/cooperation area, including suggestion of communication partners and team constellations, either by identifying neighbours or by identifying differences.

In order to illustrate the proposed approach, we introduce an example that will be referred to later. Our scenario comprises a learning environment including a wide communication/cooperation area which is connected to the learning section in the sense of learners having to cooperate and work in groups to solve tasks. Group formation and partly also selection of tasks is to be done by the system but can be revised by an administrator or tutor. Students should be grouped according to their learning and communication/cooperation behaviour. Thus, the system must be able to observe and characterize an individual's learning style, level of activity, activity patterns characterizing cooperative learning and communication habits in order to predict the performance within a group. Additionally, the system has to be capable of rating cooperation among learners in order to identify and address problems in this area.

Some of the steps described cannot be readily implemented using a rule-based system, because it cannot discover novel patterns at run-time by itself – expressing such patterns in rules requires a large investment in human resources for activity observation and interpretation, and high levels of expertise in formulating the resulting rules. CI approaches can be helpful in discovering patterns with no or little human intervention and automatically creating computable representations of these patterns. This would, in turn, enable easier integration of new adaptation knowledge with minimal input from the developers. As often CI entails the problem of the developer losing control about the system's actions, it is important to use techniques that allow keeping the processes transparent (section 5).

4 Information to Be Collected

Information retrieved by the system and used as input for CI approaches includes: users' online time, actions related to communication/cooperation (handling read, write, update, delete actions separately), users' current knowledge, and learning activities (e.g. the time users need for a test, the time spent on the content before taking a test, the performance in a test), etc. In addition to this kind of data which is observable relatively easily, the content of communicational activity can also be of interest. Many of these information units are interrelated. To find out patterns and dependencies is the system's task. There are several questions that are interesting: How is a user's time spent on communication related to the learning curriculum? Does the knowledge state influence communication/cooperation activity? What is the degree of similarity between a user's activity level in the communication/cooperation area and in the content area? How active or passive is a user in general?

These pieces of information provide a promising basis of data in order to achieve the intended forms of adaptation. Yet, there are some potential challenges to be aware of. First, we have to consider that learner behaviour and cognition/learning are actually related. Each person might just have an idiosyncratic collaboration behaviour that works best for that person but we must not eliminate that in some cases this is not transferable to others. Second, the communication/cooperation behaviour that learners show is not necessarily good or optimal behaviour. Additionally, behaviour also depends on the tool – changing the tool to an adaptive version may also lead to changes in the behaviour.

5 Technologies

In this paper we will focus on pure neural networks, combined neuro-fuzzy approaches and Bayesian networks as representative CI approaches. These techniques were chosen because of characteristics making them suitable for our scenario (see subsections) and compose an initial set that may still be extended later.

5.1 Neural Networks

Artificial Neural Networks (ANNs) are biologically inspired simulations of physical neural networks.

The proposed approach involves employing a custom combination of supervised and unsupervised learning ([Sison and Shimura, 1998], [Amershi and Conati, 2007]) to relate activity patterns with desired outcomes. This will be achieved by providing the system with success and failure "indicators" that are used to characterize group work and outputs. When applied over a multitude of users and groups for certain types of tasks, the network will start isolating the factors that may lead to positive (or, conversely, undesirable) outcomes in the given task context. For instance, a high level of communication may be found to be a prerequisite for successful joint work on a specific task. An ANN working as described can not only discover activity clusters but also adapt its components (meaning changing link weights and eventually activating new neurons), and, more importantly, it does so without depending on continuous human intervention. Humans don't have to undergo the whole process of detecting patterns, putting them into rules and feeding them back into the system. Instead, they can define desirable outcomes and let the ANN work towards learning what activity patterns lead to them; they can also assess the results and choose to perform corrections akin to supervised learning to fine-tune the network's operation.

5.2 Neuro-Fuzzy Approaches

ANNs have a lot of advantages but also some drawbacks. Often processes are not transparent enough to observe the network's behaviour, i.e. the hidden sector can turn to be some kind of blackbox. This can make it hard or even impossible to transfer results to other scenarios. Most ANNs are lacking explanation capability [Andrews *et al.*, 1996], i.e. they are able to find solutions to problems but are hardly able to reason about them. Rule extraction is more complicated than with other technologies (but possible [Taha and Gosh, 1996]). Because of these issues, ANNs are likely to be used with other technolgies in an integrated approach. For us, an ANN can be an excellent "frame" (cf. characteristics in section 5.1) but can achieve more transparent and better transferable results if applied in combination with another technique to circumvent the "blackbox-syndrom".

Fuzzy modeling is based on a rule structure and is well applicable for inference systems if human expertise at a high level is available for rule definition, evaluation and adaptation. Fuzzy logic can be combined with ANNs in order to take advantage of their respective strengths and overcome their weaknesses (e.g. approaching a more transparent "hidden" layer). This is achieved by extracting the fuzzy inference engine from the fuzzy system and integrating it in the ANN but keeping the ANN's ability to learn and autonomously adapt its behaviour.

5.3 Bayesian Networks

A Bayesian Network (BN) specifies dependence properties between variables (probabilities for values are conditioned on the variable's parents). Learning has been an important research issue also within this field (e.g. [Heckerman, 1995]). The main idea is to refine the network structure and probability distributions based on given data.

BNs hold promise for implementing adaptivity in e-learning systems, e.g. because they allow the combination of domain knowledge and data. This is relevant in order to feed the system with information before much data is available. A BN can also derive causal relationships [Heckerman, 1995] by correlating facts (e.g. a low participation value of a group member and a related document not being ready in time). This is important in e-learning where it is often hard to define the correlations between learning and cooperation activity. The BN is in most cases fed with data that has gone through preprocessing; it does not have to continually correlate all pieces of information. Yet, the BN must be able to do simple correlations (e.g. determine a learner's activity level). In our example, a BN is potentially capable of solving the classification problem because it can discover clusters of similar paths and can therefore define patterns autonomously that may be revised by humans later. A BN is also able to include new domain knowledge, occasionally updating probability distributions.

6 Previous Work

Although a lot of work has been done in the area of adaptive systems in the past decades, also within the e-learning sector, there was not much activity concerning adaptive systems based on technologies like ANNs or BNs. Still, even if there is no big community for CI within the adaptive systems field, there have been attempts to combine both. For example, [Vasilyev, 2002] gives a detailed summary of the theoretical background of new approaches (including ANNs) for learning classifier systems. [Goren-Bar *et al.*, 2001] evaluate an approach using a self-organizing map. [Webb *et al.*, 2001] give an introduction on machine learning for user modeling, identify characteristics of user modeling in relation to CI, and point out challenges to be faced. [Stathacopoulou *et al.*, 2003] present an ANN-based fuzzy modeling approach to assess knowledge. [Amershi and Conati, 2007] and [Sison and Shimura, 1998] focus on the description and evaluation of machine learning approaches. Their work will also be used as reference in order to specifically apply CI to adaptive systems in the e-learning sector.

7 Conclusions

Summing up, the usage of CI technologies in user modeling can definitely contribute to improved adaptation and reduction of human effort to ensure quality and "up-to-dateness" of model data. These approaches can address problems simpler ones are having with (semi-)autonomous pattern recognition, classification and evaluation at run-time. In e-lerning there are scenarios where a system should be able to predict users' behaviour not only based on test results (this can also be achieved by a simpler technology), but also on correlations of a user's activity in communication, the way of learning or working in a team with the actual learning performance. Thus, e-learning is an excellent application environment for CI in adaptive systems.

The full integration of such approaches into an existing environment and evaluation in a "real-world" scenario will be performed within a related PhD thesis. Adaptivity in e-learning is much more popular in the research area than within well-known and -established e-learning platforms ([Hauger and Köck, 2007]). Thus, it will be an interesting contribution to the field of adaptive e-learning to bring adaptivity into a widely-used system ([Sakai, 2008]) and apply advanced technologies of CI where until now simpler but more limited approaches have been dominating.

Acknowledgements

The work reported in this paper has been partially funded by the Socrates Minerva "Adaptive Learning Spaces" (ALS) project (229714-CP-1-2006-1-NL-MPP). For information on the ALS project please refer to the project's web site: http://www.als-project.org

References

[Amershi and Conati, 2007] S. Amershi and C. Conati. Unsupervised and supervised machine learning in user modeling for intelligent learning environments. In *Proc. of the 2007 Int. Conf. on Intelliget User Interfaces*, 2007.

[Andrews *et al.*, 1996] R. Andrews, J. Diederich, and A.B. Tickle. Survey and critique of techniques for extracting rules from trained artificial neural networks. *Knowledge-Based Systems*, 1996.

[Brusilovsky and Peylo, 2003] P. Brusilovsky and C. Peylo. Adaptive and intelligent web-based educational systems. *Int. Journal of Artificial Intelligence in Education*, 2003.

[Goren-Bar *et al.*, 2001] D. Goren-Bar, T. Kuflik, D. Lev, and P. Shoval. Automatic personal categorization using artificial neural networks. In *Proc. of the 8th Int. Conf. on User Modeling*, 2001.

[Hauger and Köck, 2007] D. Hauger and M. Köck. State of the art of adaptivity in e-learning platforms. In *LWA 2007, Workshop Proceedings*, 2007.

[Heckerman, 1995] D. Heckerman. A tutorial on learning with bayesian networks. Technical report, Microsoft Research, 1995.

[Sakai, 2008] Sakai. http://www.sakaiproject.org, 2008.

[Sison and Shimura, 1998] R. Sison and M. Shimura. Student modeling and machine learning. *Int. Journal of Artificial Intelligence in Education*, pages 128–158, 1998.

[Soller, 2007] A. Soller. Adaptive support for distributed collaboration. In *The Adaptive Web*. 2007.

[Stathacopoulou *et al.*, 2003] R. Stathacopoulou, M. Grigoriadou, and G.D. Magoulas. A neuro-fuzzy approach in student modeling. In *Proc. of the 9th Int. Conf. on User Modeling*, 2003.

[Taha and Gosh, 1996] I. Taha and J. Gosh. Three techniques for extracting rules from feedforward networks. In *Intelligent Engineering Systems Through Artificial Neural Networks: ANNIE*, 1996.

[Vasilyev, 2002] A. Vasilyev. Synergic approach in adaptive systems. Master's thesis, TU Riga, 2002.

[Webb *et al.*, 2001] G.I. Webb, M.J. Pazzani, and D. Billsus. Machine learning for user modeling. *User Modeling and User-Adapted Interaction*, 2001.