Activity-Based Learner-Models for Learner Monitoring and Recommendations in Moodle

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Abstract. In technology-enhanced learning, activity-based learner models can provide evidence for competence assessment. Such models are the foundation for learning and teaching support, such as: adaptation, assessment, and competence analytics, recommendations, and so on. This paper analyses how to construct activity-based learner models based on existing data in the Moodle learning management system. Based on the activity theory model and the actuator-indicator model, aggregators of learner activities for different activity types were implemented in Moodle. This requires the consideration of the social roles in a course, in order to enable adaptive views for learners and instructors on the stored activity information. The implementation showed that Moodle stores information about course activities that requires filtering before it can get used for higher level processing. The social planes in Moodle reveal a higher complexity than it has been previously described by theories of classroom orchestration, such as actors who are no longer present in a course.

Keywords: Activity-based learner models, Moodle, Learners tracking, Learning analytics, Competence assessment, Indicators, TEL recommender systems.

1 Introduction

In Virtual Learning Environments (VLE), rich user models based on activity traces are required for different types of personalized learning support such as: analytics of competences' development, activity-based smart indicators and recommendations. The general process could be described as the record of data interactions and outcomes of activities, the semantic interpretation of collected data and their analysis to produce appropriate support responses.

The Learning Management System (LMS) Moodle records a broad range of individual learners' traces in real time. For adaptive systems these interaction footprints had been used to produce new learning paths [1]. However, this data is not easily accessible to Moodle users and the analytics based on this data are hidden to

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students and poorly provided to teachers. This hinders practitioners to apply real time educational data in their practice. Although the increasing amount of learning analytics (LA) related papers published nowadays [2], research contributions about how automatically collected activity traces could be effectively used for supporting learning process are rare.

The research presented in this technical-design paper is the foundation for future work on applying the concepts of learning analytics for competence assessment and recommendations. This contribution focuses on the concept of social planes and analyses social perspectives for accessing Moodle's tracking data. The paper analyses the reuse of Moodle's tracking data for learner and group modelling. Moodle activity log is used to build rich learner models based on learner activities within a social context. Therefore, this paper addresses social facets of Moodle's log data and their implications for learning support. We have implemented an architecture that based on the Activity Theory model [4] and the actuator-indicator model [3] to have a flexible and extendable interface to Moodle's tracking data for different roles in learning processes. The resulting framework transforms the collected data into learning analytic information for the *social planes* "self", "peers" and "class". Furthermore, the implementation considered different *social perspectives* on the data. At this point these perspectives are coupled to the course roles "student" and "teacher". The concept of social perspectives on tracking data is useful to integrate aspects of privacy and data-protection while modelling learning analytics functions.

The social contexts of the initial implementation were grounded on social planes that have been identified by prior research on instructional design and on collaborative learning. First tests revealed that the given conceptualisations of social planes in education did not fully describe the tracking data of the Moodle logs.

This contribution has the following structure. Section 2 outlines the state-of-the-art about technology-supported competence-assessment. Section 3 presents the research objective. Section 4 analyses an implementation of activity-based learner models and learning analytics in Moodle. The implications of the prototypical implementation for technology-supported assessment are discussed in section 5. Section 6 presents the findings. Perspectives towards recommendations support are analysed in section 7. Finally, this paper concludes with an outlook on future research in section 8.

2 Background

Most VLEs already provide functions that can be used for supporting activity-centred learning, but the related information is commonly unavailable in a structured form. Semantically structured learner models are required in order to provide technological support for more activity-centred assessment types. An *activity-based learner model* creates a semantic structure of dynamically generated learner properties that reflect observed actions of a learner. Activity-based learner models are a prerequisite for activity-centred assessment and process support for competence development.

Contemporary competence models such as PALO [5] and EQF [6] describe proficiency levels of competences according to types of activities that learners are capable to perform. Previous research proposed [7] and implemented [8] the Adaptive Evaluation Engine Architecture (AEEA) for competence assessment. This architecture emphasizes the process factors for assessing competence developments over content-centred factors of conventional outcome-based assessment approaches.

Cheetham and Chivers [9] define a *competence* as knowledge- or theory-guided practice. This implies that a competence can be recognized only if it is demonstrated, reflected and used for guiding practice. In contrast to a *skill* that focuses on instrumental actions such as handling a specific tool, a competence requires more profound conceptual understanding of the underpinnings of the related practices as well as experiences in applying this understanding. Furthermore, a *competence* differs from a *competency* in so far that the former refers to the ability of linking knowledge with practices whereas the latter refers to knowledge about practice [9].

The *assessment of competence development* relies on evidence that learners are able to perform actions that are related to a competence. This perspective emphasizes the relevance of the process for its results. Previous research suggested *outcome-centered* testing as formative assessment of competence developments [10]. However, these approaches appear to be limited, because of the active nature of competence development.

The present study is grounded on two models: the Engeström's Activity Theory and the Actuator-Indicator model as pillars to implement an activity-based learner model in Moodle.

2.1 Activity Theory

Engeström's Activity Theory has its origins in modelling and analysing business processes [4]. The core underpinning of the activity theory is that activity cannot be limited to "means of getting to results" but needs to be analysed at the level of actions. The Activity Theory provides a system model to describe actions and their contextual constraints. This model has six components: A subject, an object, instruments, rules, social planes (community), and co-operative processes (division of labour). The interplay of these components leads to an outcome of an activity. The activity system can be separated into an action part and a context part. The relations in the action part describe the observable interplay of the elements in an activity. The subject, the object, and the instruments are part of the action part. The relations in the context part describe supporting and constraining factors for an activity. This part contains the rules, the social planes, and the co-operative processes.

The Activity Theory model describes the structural relations between the components of a single activity. Each element of this model may relate to individual activities that can be described with the model recursively. Additionally, the activity's outcome can trigger new activities. This allows the systematic description of complex processes. This model has been used to analyse the effectiveness and the efficiency of business processes for identifying potential improvements of work settings.

The Activity Theory has received some attention by TEL research, most notably in the context of Computer Supported Collaborative Learning (CSCL) [11]. The concepts of Activity Theory are attractive for educational-technology research because they share key aspects that have been identified by instructional design research [12]. The provided relationship model connects these aspects systematically. In educational settings the elements “teacher” and “learner” replace the “subject” and the “object” of the original model.

Dillenbourg [11], [13], [14] argues that social planes require consideration for orchestrating technology-enhanced learning. These planes are bound to the social connectedness of learners on the activity level and can include the individual, collaborative, collective (class wide) activities. Dillenbourg [13] identifies 5 generic social planes that structure or influence learning activities: the individual plane, the group plane, the class plane, the community plane and the world plane. The individual plane refers to solo activities. The group plane refers to activities in small groups that allow direct collaboration among all participants. The class plane includes activities that involve all participants from the same course. The community plane involves actors from other classes or courses on the same topic. Finally, the world plane refers to actions that involve unidentified actors, such as visitors of a public web-journal.

Glahn, Specht and Koper [15] have identified that activity information from other social planes influences the awareness and the self-regulation of learners. They identified that contrasting individual learning activities with the same information about activities on a different social plane enables learners to contextualize their own activities and stimulate the social awareness with regard to the activities undertaken on the other plane. This indicates that information of different social planes can support self-assessment activities in TEL.

The second aspect of the Activity Theory is that rules define and constrain an activity. This aspect focuses on the *contextualising factors* of an activity. In TEL rules on learning activities are commonly perceived as part of instructional design problems. This is mainly due to the fact that rules are an integral part of every instructional design [12], [16]. However, Verpoorten et al. [17] highlighted that rules in VLEs constraining learning activities can be located at several hierarchical control levels, namely, the system level, the organizational level, the teacher level, and the learner level. The hierarchy of these levels means that the rules at each level constrain the possible activities of the following levels. These levels also involve stakeholders such as system developers, technical administrators or organizational managers, who are typically ignored by TEL research.

While in Engeström’s original model instruments are considered as passive mediators in an activity, the different types of rules directly affect these instruments in the activity system. In interactive information systems, actors often do not apply these rules directly. More commonly external rules constrain the possible use of an instrument, such as a VLE. These external rules can be inherent to an instructional design, hardwired into the logic of an information system, or configured as part of an organisational policy. These rules are included through the instruments that are used in an activity. In the same line of reasoning, these technology-related constraints can have a direct impact on collaboration and co-operation in learning processes. This technology-induced change suggests an extension of the original Activity Theory model that also considers the relations between procedural rules, instruments, and collaborative processes (Fig. 1).

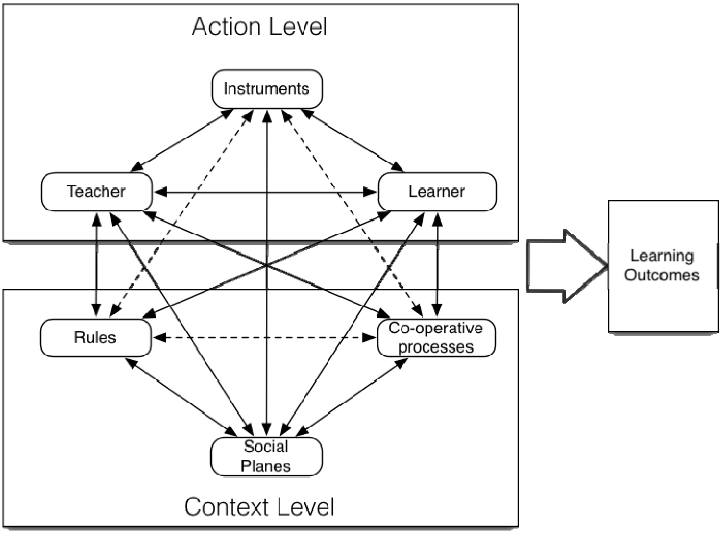

Fig. 1. Extended Activity Theory Model
(dashed lines refer to extended relations)

Outcome-based assessment focuses [10] on the results of an activity and tries to deduce the success of an activity by comparing expected and delivered learning outcomes. The activity itself remains a black box for such approaches. *Activity-based assessment* changes this perspective towards assessing the activities that lead to the outcomes. This includes the assessment of the appropriate applications of external rules, the interactions on and across social planes, and (if present) collaboration and co-operation among learners. All aspects of this kind of assessment contribute to the evidence that learners achieved the targeted competence levels.

From the perspective of the extended Activity Theory model the provisioning and exposure of analytical rules for accessing data in information systems remains a challenge for the effective application of learning analytics for supporting learners and teachers.

2.2 Actuator-Indicator Model

While the Activity Theory offers a well-structured model for analysing and conceptualizing learning and its assessment, it does not provide guidelines for implementing services for supporting learning or assessment. Zimmermann, Specht and Lorenz [3] have proposed a generic system architecture for adaptive and contextual systems. Further research [18], [19], [15] has extended this architecture with concepts of motivational research and applied it to different application areas of TEL [15], [20], [21].

The model proposed consists of four functional layers of an architecture. The core functional layers are sensor data management (sensor layer), context abstraction (semantic layer), the control of actuator output (control layer), and the indication of the output (indicator layer). Fig. 2 shows the information flow of the actuator-indicator model. The *sensor layer* is responsible for logging information about traces of learners' interactions and other contextual information.

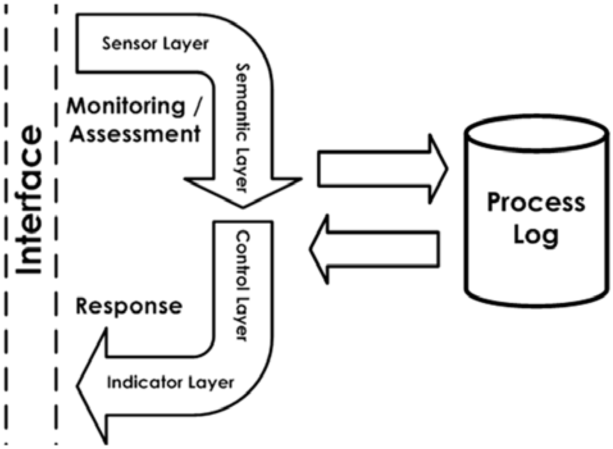

Fig. 2. Actuator-indicator model Zimmerman, Specht & Lorenz, 2005

The *semantic layer* collects the data from the log system and aggregates this data into higher-level information. An *aggregator* is a function that transforms sensor data from the log system. An *aggregator of activity* refers to how logs of a particular activity are semantically transformed. The aggregators respond differently depending on the context (social plane), in which they are called. The *control layer* is in charge of interpreting the response of aggregators through different *strategies*. A *strategy* determinates when and how to collect aggregator responses and how to present them to the user. In brief, the active strategy selects the representations and provides the aggregated information to them. To complement this definition, an *activity-based learner model* integrates the output of several aggregators. Finally, the *indicator layer* is in charge of transforming the returned data of the control layer into representations that are interpretable by humans.

For integrating learning analytics capabilities to complex legacy systems it is a challenge to identify existing functions and components along the information processing flow of this architecture.

3 Research Question

The main research question of this study addresses the need for structuring complex data resulting from activities in a learning environment. Moodle, like other VLEs, has only limited built-in support for learning analytics. The core components and extensions related to assessment focus on outcomes rather than the activities.

Therefore, the question is: how to introspect learning activities for competence assessment and recommendations?

Integrating the concepts of the actuator-indicator model with the Activity Theory approaches this question. This integration is an attempt of structuring learning analytics techniques for designing solutions for activity-based assessment and recommendations that can be used by teachers and instructional designers in TEL.

The core of this question is primarily related to the semantic layer of the actuator-indicator model. An aggregator in this layer can be defined in terms of the Activity Theory as a *rule* that enables *perspectives* on activities that are performed on one or many *social planes (s.)*. As such every aggregator can be verified regarding its meaning for a perspective on a social plane. Figure 3 highlights the previous concepts within the extended Activity Theory model.

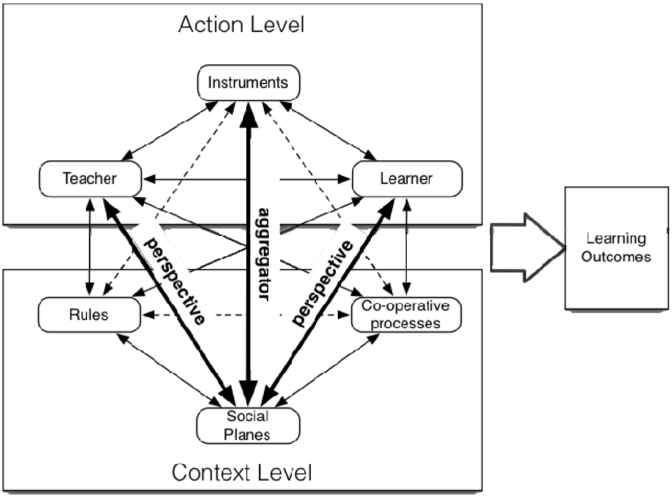

Fig. 3. Research scope in relation to the Extended Activity Theory Model

4 Architecture for Learning Analytics and Recommendations

The translation of Engeström's model [4] to TEL, described in section 2.1 along with the layered structure of [3], described in section 2.2, are permeated in this section to propose an architecture to support learning analytics and recommendations. Figure 4 shows the layout of the overall architecture. The architecture uses the context information present in Moodle and adds some other components. The architecture allows the construction of dynamic learner models based on perspectives over social planes in activities. The models need to be capable of reacting to actions during the learning process.

The proposed architecture builds on the layers proposed by [3]: Sensor layer, semantic layer, control layer and indicator layer. The activity-based learner model is related to the first two layers and the learning analytics solutions to the last two layers. In this section the components of the architecture are explained in relation to these two parts.

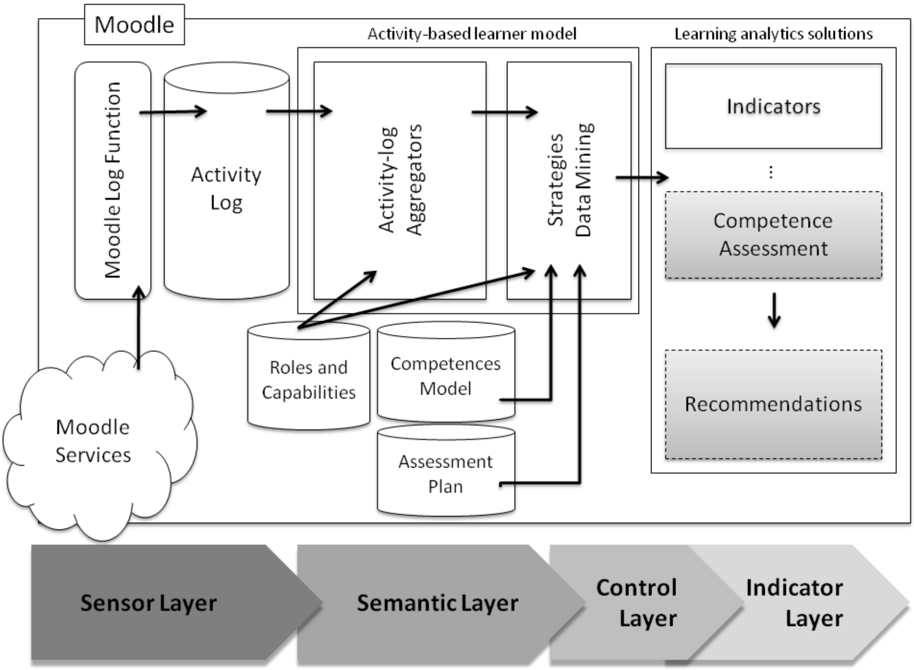

Fig. 4. Architecture to support activity-based learners models in Moodle

4.1 Activity-Based Learner Models for Moodle

The Sensor Layer. The purpose of this layer is to collect and to store traces of actions. Learners perform activities in Moodle. Moodle implements a detailed activity logging in its services. Consequently, it is not necessary to implement a separate sensor layer for tracking learner actions in Moodle, because the system already stores sufficient context information about the learners' interactions. Logs in Moodle are created by the Moodle Log Function and stored in mdl_log Moodle database, which stores all interactions and allows structured querying and filtering of this data. This data can be used for identifying complex activities by integrating the access time, the active user, and the performed action.

By default only system administrators and teachers have access to activity reports and basic statistics in Moodle. Some research about the use of Moodle Log Function were made previously by [17] and [20]. Verpoorten et al. in [17] delineated and documented a perspective on personalization based on the mirroring of personal tracked data to the user; [20] is a conceptual paper which analyses the underlying concepts for a system-architecture for device adaption for mobile learning, integrating Moodle into ubiquitous computing. In addition, tools for teachers and administrators feedback in Moodle are the report logs and the report statistics. The Moodle log reporting and statistics are drawn from the mdl_log database.

The Semantic Layer. This layer processes the data collected by the sensor layer into semantically meaningful information. At the level of the semantic layer several aggregators can be active to process the traces of learning activity. The following aspects constitute an aggregator.

- An Aggregation rule represents an SQL query that processes Moodle's user tracking database. Each aggregation rule returns the result data to the JSON format that can be easily interpreted by web-frontends. Each aggregation rule can get accessed through a distinct name that represents the analytic function of the rule.
- The context is used for filtering a social plane of the learners. The social planes implemented so far are: self, peer and class. The context "self" includes only the data of the learner, who requests the data from the Moodle system. The context "peers" includes the data of all other learners who are enrolled in the same courses as the learner excluding the data of the current user. The context "class" includes all learners who are enrolled and active in the course. The context is passed as a parameter to the aggregation rule.
- Role-based perspective on the data is automatically applied based on the current role of the requesting user. Students have only access to the contexts 'self' and – annonymised – to those of the 'peer' context. Teachers have access to all details of the aggregated information. When teachers make a request using the context 'self' or 'peer' an extra parameter is required for identifying the related student for whom this context will be applied.

The current system implements the semantic layer as a REST service through which the different aggregators have unique names and can be directly accessed through an URL. The implementation of the Strategy Design Pattern [22] is planned for future releases in order to access the aggregators through a facade. In summary, each aggregation rule can be limited to a perspective over a different social plane of the learner and to a specific course.

Other semantic information is stored in the Moodle database. For instance, in order to support competence development and competence assessment, the semantic layer requires a competence model and an assessment plan [7] [8]. Tables to express the competence model based on the European Qualification Framework [6] were created for the semantic layer. Similarly, tables to express the assessment plan were integrated. The competence model defines the ontology of competences, their levels of qualification and activities related to each level of competence. The assessment plan defines how actions in a course relate to the competence model and how they contribute to the evidence on the competence development of a learner. Other examples of semantic information stored in the Moodle database are the structure of roles and capabilities to classify the type of users and theirs permissions in the system. The capabilities in Moodle can be applied to many levels such as: activity, course, system and so on.

4.2 Learning Analytics Solutions

The *Control Layer*. This layer defines the arrangement of the aggregators and the visualizations that are used for mirroring. The control layer is implemented as a plug-in that provides several widgets that can be independently integrated into the user interface of a course. Each widget contains a set of aggregators and visualizations, which can be configured by the instructor of a course. Through a context parameter an instructor can define the scope of the data that is returned by the selected aggregator. In the case of recommendations an aggregator implements the data mining algorithms. In this layer the competence model and the assessment plan are data inputs to process the recommendation strategies and the indicators of competence analytics. The competence analytics will be implemented in further research. Section 5 analyses this aspect in depth. A recommender system is planned for further research. Using this architecture, these recommender systems will be base on learning analytics. Section 6 analyses this aspect.

The Indicator Layer. This layer provides different presentation modes for the data of the control layer. The indicator chooses the presentation mode based on the configuration of the indicator layer and receives the data from the control layer. So far the indicator layer shows smart indicators whose parameters are the context and the tracked activity. The indicator layer is embedded into the user interface of Moodle through a JavaScript.

5 Prototype Application

Prototypes of aggregators using the proposed architecture for Moodle were implemented. Each aggregator allows introspecting a particular activity type. The aggregators and related control rules are based on learning analytic functions that are accessible to the users through indicators [18]. An indicator offers different forms of "visualising" the data provided by one aggregator.

In the teacher's interface it is possible to configure and arrange indicators. This interface allows to select and to configure the aggregators that will be used with an indicator. These configurations are stored at the level of the control layer. A "yardstick" indicator also allows using two social planes for the same aggregator that enables students to compare their actions to those performed at the other social plane. The student interface reads the teacher configured indicators and displays the learning analytics information accordingly.

6 Findings

The initial version of aggregators implemented the data aggregation solitarily at the level of the log database. The core assumption at this level was that students in a course have an "enrolment" marker in their activities for the course, whereas teaching staff has no such marker. During tests of the aggregators on a fully deployed course the aggregators returned 22 students for the "class" plane, while Moodle's course administration reported only 15 students for the course. The first check revealed that no teaching staff was among the additional participants, which implies that the first assumption for filtering the activities in the log database was correct. A more focused analysis of the participants reported in the two interfaces together with the related course manager showed that the additionally reported students were former participants that were no longer enrolled in that course. However, for these participants no “unenrollment” marker could be found in the activity logs.

Based on these insights a second version of the aggregators have been implemented. In this version the social planes were based on the role assignment of a course. As expected this version returned data that was consistent with the data presented in the course administration.

On the first sight this test protocol appears like an ordinary bug related to a wrongly applied database query. From a learning analytics’ viewpoint the results indicate that relying entirely on activity tracking in Moodle is not sufficient for providing accurate data that is related to the social planes that were identified by prior research. Instead of only active users the activity logs also reported information for former participants of the same course. These participants can be “drop-outs” that have failed course requirements at some intermediate point or “alumni” who have already completed and left the course. Both groups cannot be discriminated from the information provided by Moodle.

The analysis of the returned data indicates that the initial assumption regarding the “enrollment” marker was indeed correct because no participants with other (former) roles were returned. One important insight from this study is that prior research concerning social planes considered courses as stable social structures. This view is supported by the course administration of Moodle. However, the unexpected results of the initial tests highlight that the social planes that are found in Moodle systems are of greater complexity of social planes than it has been previously described by theories of classroom orchestration. Furthermore, this historical data can offer new perspectives towards learning analytics and recommendations. This opportunity is discussed as part of the following section.

7 Perspective towards Activity-Based Learning Analytics

This section outlines some possible extensions of the activity-based learner model for Learning Analytics solutions. We cluster this section along two questions (a) What kind of formative feedback could be delivered from activity-based learner model for running courses? And (b) How historical data of former students can help to produce new useful learning analytic solutions? For both questions we refer once again to the proposed architecture presented in Fig. 3.

Regarding question one, teachers and students can benefit from a combination of different indicators to help gauge whether or not a certain competence was successfully attained. Different kinds of comparative indicators about assessment results, expected knowledge levels versus achieved knowledge levels, and the develop of competences can be combined in order to draw a more complete picture of the learning process and assess the quality of the achieved competences. For example, a teacher could combine the outcome of a group project – e.g., a joined report on a particular topic – and also take into account the communication activities of the students from the group plane (e.g., forum discussions, shared files, amount of comments and annotations) that are reported and visualized in the group indicator. With this additional information the teachers not only receive the final result of the students, they can also value the group collaboration and the contribution of every single student to the joined report. This example only requires taking into account the current data created by the students of a running course.

The second question follows the idea to extend the data of a current course with historical data of students from former courses. Historical data in combination with learning analytics can be supportive to gain new insights into the running courses that would otherwise remain concealed. For instance, a drop-out detection system could recommend the teacher students that need special attention because they are in danger to withdraw from the course. It could be based on a classifier technique like decision trees, Bayesian classifiers or support vector machines [23] that are trained to learn drop-out patterns of students from former Moodle courses. The trained classifier can then be applied to running courses to identify students that show similar drop-out patterns. It could mark those students that show drop-out patterns in a list and give the tutor the opportunity to contact the students personally and ask them if they need any additional support for their studies. Alternatively, such a recommender system could offer motivating information and encouraging activities to help a student to break the drop-out pattern. Long term, such a system could potentially decrease the amount of drop-outs, improve the customer service of the University by needs driven support, and increase the amount of graduated students.

8 Conclusions and Future Research

This paper delineated and documented a perspective in activity-based learner models as semantically models for activity-centred assessment and recommendations. This approach advises the use of tracked data with social filters. The mechanics to aggregate information and its rules to deliver the response to the user interface are the core of activity-based user models. The paper contributed with a prototype that implements indicators as examples of learning analytic applications. The prototype-testing process indicated that the activity tracking of Moodle includes data about more complex social structures in the course of the VLE. In its last part, the paper contributed to the discussion of possible benefits of the approach in assessment, competence development and recommender systems. This discussion is accompanied with the analysis of the role of historical data for learning analytics and recommendations. Further elaboration of prototypes for other applications of learning analytics and recommender systems are in progress. This research contributes to the support of informative interventions during interlaced activities with dynamic learner models that are capable of reacting to actions during the learning process.

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