Processing learner profiles for smart indicators

PROCESSING LEARNER PROFILES FOR SMART INDICATORS

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Abstract

Indicators help learners to organise, orientate and navigate through complex environments by providing contextual information relevant for the performance of learning tasks. Smart indicator systems adapt their approach of information aggregation and indication according to a learner's situation or context. In this paper context is used as temporal context of the learning progress. This paper introduces an experimental scenario in which smart indicators are applied. The following section provides a definition of smart indicators that is derived from concepts of self-regulated learning and context-aware systems. Based on this definition a system's architecture for smart indicators is proposed. Based on the preceding sections, the two problems of the research questions are addressed by discussing the implementation as it is used for the experimental scenario. This paper concludes with an analysis of current learning standards regarding the applicability in the domain of open communities.

Introduction

The term lifelong learning refers to a complex process in which people develop new and extend their existing competences. While during early phases of this process, students follow mostly prepared activities and curricula provided by schools, colleges or universities. In these environments of initial education, it is often required to support transitions of learners between topics, courses and curricula. After initial education the learning environments and the learning processes become more complex. Learners do not follow pre-designed paths that are provided by learning facilitators, but constantly change between formal training, non-formal learning, and informal competence acquisition. Furthermore, the way how people learn is different to what is known in teaching and training during initial education [20]. Therefore, many learners have difficulties in recognising and valorising their knowledge and competences they have acquired throughout life [3, 16, 31].

In contrast to these observations reflective practitioners [34] have an increasing relevance on the economical success of enterprises and organisations, and also to the social wealth of nation states and societies. Reflective practitioners are drivers of the knowledge society, because they are aware of their knowledge and competences and able to apply, to adapt and to extend these competences in their professional practice. Reflective practitioners are also referred as “high skilled individuals” in policy documents. The value of these individuals for economies and societies has become undeniable, as effects such as “brain-drain” [18] can be identified from the micro-economics of a team within an organisation to the macro-economics of a nation state. Attracting alien expertise is one approach to address this problem. However, the economical stability and social wealth depends on the ability of an organisation to establish, support, and sustain a reflective culture among the majority of their members and communities.

One aspect of this problem is how to support reflection and to raise awareness on learning processes and on competence acquisition. With respect to the changing contexts and processes of practitioners, it can be argued that such support on reflection and awareness has to adapt to these changes and has to take contextual information into account. This is because of several reasons, among which the following ones are most relevant to our research. Actors depend on the availability of external information in order to organise, orientate and navigate through complex environments by utilising contextual information [7, 38]. Contextual information on the learning process has been proven as important to support the learning process. It stimulates the learners' engagement in and commitment to collaboration [4, 27, 32]; it helps to raise awareness of and stimulates reflection about acquired competences [24, 25]; and it supports thoughtful behaviour in navigation and on learning paths [36]. Despite this evidence on the role of contextual information for reflection and learning, little research has been conducted on adapting the presentation of contextual information to the changing needs of lifelong learners throughout their learning process.

During a process, contextual information is provided by what we call *indicators.* Indicators provide a simplified representation of the state of a complex system that can be understood without much training. The framing question of the research presented in this paper is the utilisation of indicators to support reflection and raise awareness on learning processes in non-formal and informal learning settings. It has been argued that indicators are part of the interaction process between learners and learning environments [17]. As such, indicators depend on information about previous learning activities and their contexts. The information processing for this purpose can be modelled as four operational layers: a sensor layer, a semantic layer, a control layer, and a presentation layer. This paper analyses the relations and functions of these layers.

The question for research of this paper is how to provide smart indicators to learners in an unstructured community environment. The answer two this question is based on two problems. The first problem is related to gather of learner information [6, 29] and develop context models [12], which then can be reported to the learners. The second problem is the modelling of context aware adaptation strategies that define which resources can be used to generate the appropriate information according to a learner's context. In this paper we address the second problem and discuss how to utilise learning technology specifications for modelling adaptation strategies.

This paper continues with introducing an experimental scenario in which smart indicators are applied. The following section provides a definition of smart indicators that is derived from concepts of self-regulated learning and context-aware systems. Based on this definition a system's architecture for smart indicators is proposed. Based on the preceding sections, the two problems of the research questions are addressed by discussing the implementation as it is used for the experimental scenario. This paper concludes with an analysis of current learning standards regarding the applicability in the domain of open communities.

Experimental Scenario

In order to develop better understanding of supporting strategies for learning interactions we implemented a web-based prototype of smart indicators. The prototype integrates indicators into a community system. This system combines the community member's web-logs, del.icio.us[1] link lists and tag clouds. The indicator provides information on the interest and the activity to the learners. It contains two core components: An interest tag cloud and an overall activity chart. To maintain these indicators the system tracks selection activities, tagging activities, and contributions. The system adapts the presented information according to a learner's activity and interest level: It provides richer information the more a learner contributes to the community. Therefore, new participants will have different information indicated than those who contribute regularly to a community. The community system acknowledges that its participants might already use a web-log or del.icio.us instead of offering similar services. However, it is not a requirement for participation to have both. When learners register for being "members", they can provide a URL to a feed address of their web-log and their nick-name on del.icio.us. This *personal profile* is later used for creating a *learner model.* Therefore, the community system provides only a portal to recent contributions, while the actual content is external to the system.

Each action within the system is considered as a learning activity and learners score "learning points" with each action they perform in order to indicate their learning progress. However, some actions require more effort than others. For example, accessing content provided by other users is easier to perform than contributing content through a web-log. Because of these differences, the actions have different scores.

The indicator system is based on immediate and delayed interaction monitoring by interaction sensors. Immediate monitoring is implemented only for selections (so called click-through), through which the system gathers information about requests of web-log entries or links from the link list. Data about contributions is accumulated from RSS2[2] or ATOM[3] feeds independent from a learner's actions on the user interface. Information on the collected links and associated comments is gathered through del.icio.us' RPC interface[4]. The tagging activities are extracted from the data on tag clouds that is

[1] http://del.icio.us
[2] http://blogs.law.harvard.edu/tech/rss
[3] http://tools.ietf.org/html/rfc4287
[4] http://del.icio.us/help/json/

provided from both the link lists and the learner's web-logs. A learner tags an external link or a web-log entry if a tag is added to the contribution.

The semantic layer of the prototype provides two aggregators: an activity aggregator and an interest aggregator. The semantic layer analyses the sensor data according to a definition given by the aggregators. Different to the sensor layer, the semantic layer is not limited to organising incoming sensor data, but it uses the aggregators to *transform* the sensor data into meaningful information.

The control layer defines how the indicators adapt to the learner's behaviour. The prototype implements two elemental adaptation strategies. The first strategy aims at motivating learners to participate to the community's activities. The objective of the second strategy is to raise awareness on the personal interest profile and stimulate reflection on the learning process and the acquired competences. The prototype adapts the strategies according to a learner's participation to the community.

The purpose of the indicator layer is to integrate the values selected by the control layer into the user interface of the community system. The indicator layer provides different styles of displaying and selects an appropriate style for the incoming information. Two graphical and one widget indicator are provided by the prototype. One graphical indicator is used during the first level of the control strategy. This indicator shows the amount of actions for the last seven days. A second control strategy uses a different graphical indicator. It displays the activity in comparison to the average community member. The maximum value of the scale used by this indicator is the most active community member. Finally, the indicator layer provides a tag cloud widget for displaying the interests of a learner. In principle this widget is a list of hyperlinks. The tag cloud indicates higher interest values for each topic through the font size of the related tags.

Fig. 1. Sample Indicators on different strategy levels

Defining indicator systems

In the introduction we have highlighted some principles of indicators. With regard to learning technology feedback and recommender systems meet these principles. Therefore, it is necessary to distinguish indicator systems from them. Feedback systems [30, 33] analyze user interactions to inform learners on their performance on a task and to guide the learners through it. Recommender systems analyze interactions in order to recommend suitable follow-up activities [1]. The objective of both system types is to affect a learner's future activities by providing useful information. Both approaches are tightly coupled to goals or processes that are shared within a learning community. In contrast, indicator systems provide information about past actions or the current state of the learning process, without making suggestions for future actions. Having these considerations in mind, we define indicator systems as follows.

An indicator system is a system that informs a user on a status, on past activities or on events that have occurred in a context; and helps the user to orientate, organize or navigate in that context without recommending specific actions.

Humans actively search for relations to their previous interactions, in particular for indicators that provide information on the success and the value of their actions, if their actions depend on strategies that require alignment during the interaction process [21, 38]. In other words, people continuously seek for indicators that help them to verify or modify their actions, tactics and strategies. Thus, indicators on learning are important facilitators of these processes and are based on three general principles [13, 24, 26].

- Indicators rely on monitoring of the learning actions and the learning context.

- Indicators have to adapt according to a learners’ goals, actions, performance, outcomes, and history as well as to the context in which the learning takes place.
- Indicators are responses to a learner's actions or to changes in the context of the learning process, where the response is not necessarily immediate.

Most indicators implement a static approach of providing information to learners rather than adapting to the learning process [9, 15, 19, 22, 24, 28]. These approaches are considered as static according to the third principle. In contrast, *smart indicator systems* adapt their approach of information aggregation and indication according to a learner’s situation or context. In our setting context is defined by the temporal context of the learning progress.

An architecture for smart indicators

A smart indicator is a component of a context aware system that traces a learner’s interactions as well as contextual data in order to provide meaningful information in response to learning actions. In this section we describe a system’s architecture for smart indicators.

We applied an architecture for context aware systems as it has been described in Zimmermann, Specht, & Lorenz [40]. The architecture has four layers and specifies operations on the data and information flow through a system from the learner input to the system response (see **Fig. 2**). The layers are the sensor layer, the semantic layer, the control layer, and the indicator layer.

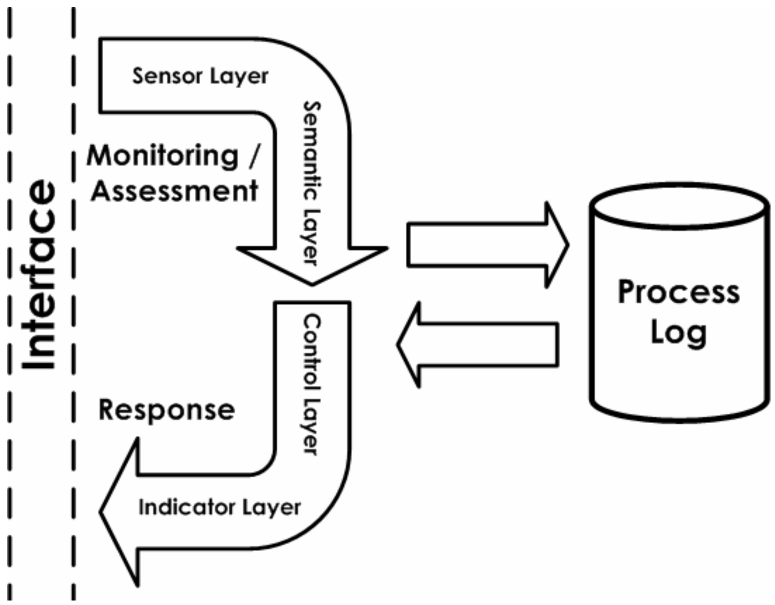

Fig. 2. Layers for context-aware information processing

The *sensor layer* is responsible for capturing the interaction footprints. A *sensor* is a simple measuring unit for a single type of data. The objective of sensor layer is to trace learner interactions. It also includes other measures that are relevant for the learning process which are not a direct result of an interaction between the learner and the system. Sensors that do not gather information about a learner’s interactions are called *contextual sensors*. Examples for contextual sensors are standardised meta-data, or tagging activities and contributions of peer-learners. In the architecture the sensor layer adds data to process log in order to allow the adaptation to the interaction history.

The *semantic layer* collects the data from the sensors and from the process log and aggregates this data into higher level information. The semantic layer defines operations or rules for processing sensor data [11]. The definition of how the data from one or more sensors has to be transformed is called an *aggregator* [12]. These rules can be named according to their meaning, for instance *activity* or *interest*. The aggregated information is interpreted by the *control layer* according to the history and context of a learner. The specific approach for interpretation is called a *strategy* [11]. It defines the conditions for selecting and combining aggregators as well as their presentation according to the learner’s context. A strategy also controls the personalization of aggregators. Finally, the aggregated information has to get presented to the learner. The *indicator layer* handles this part of the interaction. At this level the actual response is created by translating aggregated values into representations that are not just machinereadable but also accessible to humans. The active strategy of the control layer selects these representations and provides the aggregated information to them.

Many approaches in adaptive hypermedia implement adaptation on the level of the semantic layer, while the main strategy at the level of the control layer does not adapt to the learning process [e.g. 2, 5, 8, 9, 10, 15, 37]. In contrast, our approach of smart indicators adapts the strategies on the control layer in order meet the changing needs of a learner. By doing so, the adaptation strategies are adaptable to the different phases of the learning process.

In order to develop better understanding of supporting strategies for learning interactions we implemented a web-based prototype of smart indicators. **Fig. 3** shows the data-flow between the different layers of the architecture. According to the architecture the prototype has four functional layers: A sensor layer monitors the learners' activities and collects traces of interest. A semantic layer provides two aggregators to transform the data provided by the sensors. A control layer controls the indicator behaviour according to the results of the aggregators of the semantic layer. The indicator layer transforms the information into widgets that are integrated into the user interface of the system.

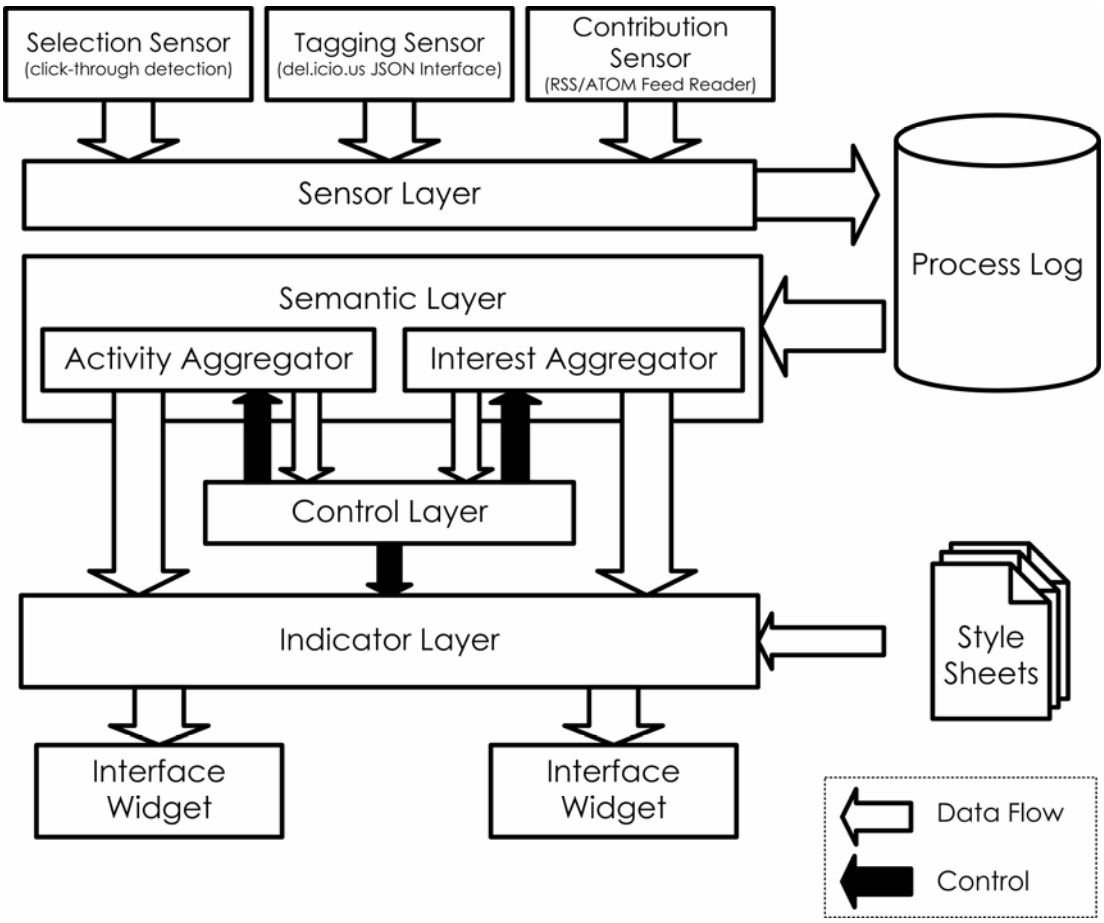

Fig. 3. Component interaction of the prototype

Learner and Context Modelling

With regard to the three defining principles of indicator systems, learner monitoring and learner modelling are central factors in the process of offering indicators for the learning process. The first requirement define that indicators rely on learner and context monitoring and the second requirement defines that indicators have to adapt to the learning progress and learning context. These requirements specify that an indicator system has to develop concepts of both the learners and the learning context. Based on this information the indicator system can select appropriate information and representations of that information for a learner.

In order to identify learning processes and changes in the learning context it is necessary to maintain a history of the learner's interactions. A learner model is basically a collection of traces of past interactions with the system. These interaction footprints can be used to assess certain factors of the learning process, such as activity or interest [14, 15, 39]. In the proposed architecture the learner modelling is performed in two steps. The first step is the data collection and homogenisation; and the second step is the semantic aggregation and assessment.

The system's view on the learners and learning context depends on the data that is available for interpretation. This underlying data is collected and homogenised by the sensor layer. The sensor layer accepts data coming from different sensors types and origins. The sensor layer clusters the incoming data into named sensor groups in order to maintain and organise the incoming data. Within a sensor group each data set contains the same type of information. For instance, in the experimental scenario a sensor collects data about which tags were used by a learner. This data may originate from the use of tags for social book-marking or web-logging; or from detected selections of links in the system's user interface. From the system's perspectives, this data belongs to the same class and is therefore organised within the same sensor group in the learner's process- log.

The sensor data is stored in a database. This database organises the incoming data in alignment with the activity notation of the IMS Learner Information Package specification (IMS LIP) [35]. IMS LIP activity information allows collecting process information on learner activities within a learning environment which is similar to a log-file.

Within the experimental scenario context is defined by learner actions in a fixed timeframe. The boundaries of context are therefore given by social and temporal constraints. The indicators relate the learner actions to this context and make these relations visible to the learner. This context depends on the learning interactions of all learners. The context model is based on anonymous learner information. This is achieved by calculating the arithmetic median of all learning actions within a fixed timeframe, in order to identify the "average" learner behaviour. Therefore, context is emerges through information processing of the learners' process-logs on the semantic layer.

Although the described approach of learner and context modelling is suitable for the experimental scenario, it is limited to social and temporal contexts. The given approach excludes spatial contexts that are defined by special sensor measures that are independent from learner actions. Examples for such independent data sources are GPS sensors or thermometers. Although we are aware of these limitations, spatial contexts were excluded from this research.

Defining adaptation strategies

On the semantic layer the sensor data in the process-log is enriched. The definition of aggregators is defined as rule-sets. For these rule-sets IMS Learning Design (IMS LD) level B conditions [23] were used as an anchor. However, IMS LD conditions support neither data sets nor arrays in properties [23], while the sensor information in the process-log is available as data-sets. By extending IMS LD conditions with simple set operations such as "sum", "average" or "range" it was possible to define the aggregators by using a well tested approach. The aggregators are referred to through unique names and are exported as global properties of an IMS LD monitoring service.

The adaptation strategies on the control layer are defined as IMS LD activities. IMS LD activities are defined by pre- and post-conditions and a set of resources that should be used during the activities. For defining an adaptation strategy the output of the aggregators of the semantic layer are used to define pre- and post-conditions for a part of the strategy. The aggregators that are used while a strategy is active are referred as resources of the IMS LD activity. The output style is also defined as a reference to the XSLT style-sheet that should be used by the indicator service.

Conclusions and further research

In this article we discussed a first prototype for smart indicators. Its implementation is based the principles of the learning interaction cycle and context aware systems. For the prototype we used IMS LIP and IMS LD to provide learner and context models and associate them with adaptation strategies. Although IMS LD provides a flexible way to model adaptation strategies as learning activities, there were limitations in these specifications for modelling contexts and aggregation rules of the learners' interaction trajectories. Although these restrictions limit the use of this approach for general cases of smart indicators, we described an experimental scenario in which the underlying principles can be tested within these limitations.

Further research will have to focus on two main challenges. The first challenge addresses the use of smart indicators for learner support. While the experimental scenario in this paper is based on reasoning, more research is required to provide evidence on those factors that affect learner engagement and motivation. The second challenge is based on the limitation in modelling context based learner support by using the existing learning technology specification. Future work has to clarify is how contexts can be modelled and how these models can be utilised in order to support learners, effectively.

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