Smart Indicators on Learning Interactions

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Abstract. Indicators help actors to organise, orientate and navigate through complex environments by providing contextual information relevant for the performance of learning tasks. In this article we analyse the requirements, present a model and an initial prototype of a software system that uses smart indicators to support learners to be more engaged in the learning process. We argue that indicators need adaptation as learners develop on their learning paths in order to support interactions throughout the learning process. We use the learning interaction cycle of Garries, Ahlers and Driskel as the underlying model and architecture to describe the interaction between a learner and a learning environment. We tested the technical feasibility of the architecture by implementing a prototype. This prototype is critically reflected on the technical and educational concepts that were implemented. We conclude this article by giving an outlook on our future research, in which we evaluate the model by applying the prototype to support learner engagement in a learning community

Introduction

When performing a learning task, people need various types of information in order to monitor the progress of the task. The basis for this 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. For instance, the fuel needle of a car is an indicator that summarizes how full the tank is and how long we can drive. Without much training we understand that it is necessary to find a filling station if the fuel needle points towards the lower end of the scale. To make the appropriate decision it is not necessary to know the size of the fuel tank, the exact amount of fuel that is left in it, or about the fuel consumption of the motor. Some cars switch on an additional light, if the fuel level falls below a critical level. Such indicators focus our attention to important facts that we miss or ignore otherwise. The telephone bell is another example for such indicators: It indicates that someone is calling on the phone, of which we would not be aware of, unless we check the telephone line actively. This leads to another characteristic of indicators: They help us to focus on relevant information when it is required, while we don't have to bother about it most of the time.

Actors depend on indicators in order to organise, orientate and navigate through complex environments by utilising contextual information [8, 45]. 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 collaborating processes [4, 31, 39]; it helps to raise awareness of and stimulates reflection about acquired competences [28, 29]; and it supports thoughtful behaviour in navigation and on learning paths [43]. Despite this evidence on the role of indicators, little research has been conducted on the problem of adapting indicators to the changing needs of the learners throughout their learning process.

The research presented in this article investigates how to make non-formal and informal learning more attractive. The main focus is on how to support learners in their engagement in and reflection on the learning process by providing smart indicators. In this article we critically reflect on our work on smart indicators: Based on the concept of context aware systems [16] and the learning interaction cycle of Garries, Ahlers, & Driskel [21] we specify the requirements of smart indicators. These requirements are discussed in the following two sections. In order to meet these requirements, we have developed a model and a system's architecture. In section four we explore this architecture and analyse the gaps in current research on indicators related to it. We tested the technical feasibility of the architecture by implementing a prototype. In the fifth section, we critically reflect on the technical and educational concepts that were implemented into this system. We conclude this article by giving an outlook on our future research, in which we evaluate the model by applying the prototype to support learner engagement in collaborative learning.

Defining indicator systems

In the previous section 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 [38, 40] 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.

It is a fundamental insight that 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. This is especially the case if the actions are based on strategies that require alignment during the process [25, 45]. In other words, people continuously seek for indicators that help them to verify or modify their actions, tactics and strategies.

Of course, this applies also to learning processes as we learn from research on feedback and self-regulated learning [8, 30, 34, 37]. Indicators on learning are important facilitators of these processes and are based on three general principles [15, 28, 30]:

- 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 [2, 5, 9, 10, 19, 20, 22, 24, 26, 28, 32, 33, 35, 36]. These approaches are considered as static as they follow a fixed rule-set to collect, to aggregate and to indicate information to learners. In contrast, *smart indicator systems* adapt their approach of information aggregation and indication according to a learner's situation or context.

Cycles of learning interactions

Indicators are part of the interaction between a learner and a system, which is either a social system, such as a group of learners who are supported by a trainer, or a technical system like software for computer supported training. A single interaction is defined by two parts: an action performed by an actor and a response to this action from the system. With regard to learning, a learning process is described as a chain of interactions: Garries, Ahlers, & Driskel [21] define the learning interaction cycle by single interactions that are connected by the interpretation of a system's response by the learner. At this level a learning process is a flow of interactions between a learner and a corresponding system. On the level of learning interaction cycles, learning processes are considered from a micro-perspective.

However, this definition of the learning interaction cycle is limited as it focuses on the learner's cognitive processes [8, 21]. Indicators are part of the interface of a system. In order to provide smart indicators "the system" cannot be simplified as a black box. Following concepts of context aware systems [14, 16, 47] interaction appears as a symmetrical process between an actor and a system that is interconnected by the system's interface (see **Fig. 1**): Each action of an actor on the interface is analysed and assessed by the system. Based on this analysis the system provides a response to the action on the interface. The actor analyses and reflects on this response to judge the results of the initial action. Further actions depend on the outcomes of this last phase [3, 21].

For learner support it is necessary to understand that each phase of the process affects the learners' engagement and performance [21, 23, 39] which is guided by reflection on actions and past experiences. Schön's [41] concept of *reflection in action* highlights also the relation of past experiences to the current situation of an actor. With regard to the learning interaction cycle, learners utilise past experiences for judging the results of their actions in the same way as smart indicators rely on the learners' interaction history.

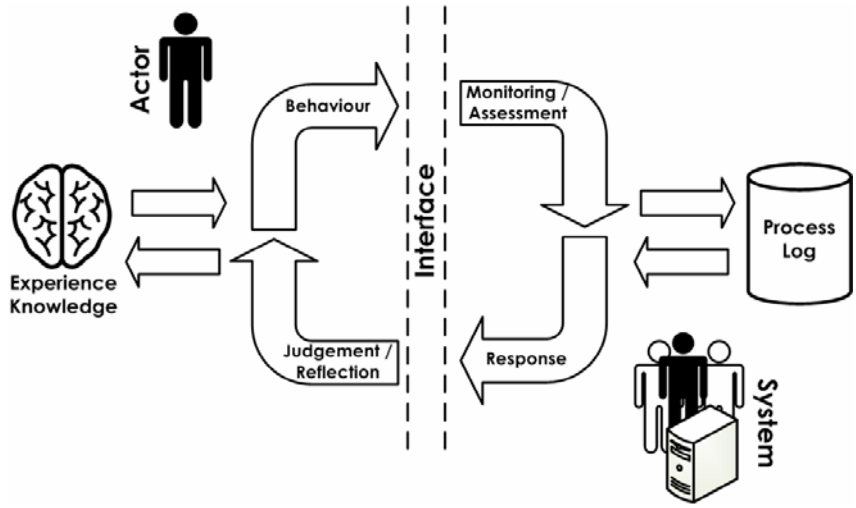

Fig. 1. Learning interaction cycle

Wexelblat & Maes [46] define *interaction history* as traces of interactions between learners and objects. The author argues that interaction history is extensively used by learners to guide actions, to make choices, and to find things of importance or interest [46]. Dron, Boyne, & Mitchell [18] use the term *footprint* to indicate the value and meaning of each interaction in creating social spaces, for which the authors introduce the term *stigmergy.* This concept was also applied for social navigation [17]. Recently, Farzan & Brusilovsky [20] use the term *interaction footprint* to refer to different traces that are left during the interaction process. Examples for such traces are notes about accessing a document in a repository, or the time a learner spent reading a document [20].

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 [47]. 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 of this architecture are the sensor layer, the semantic layer, the control layer, and the indicator layer.

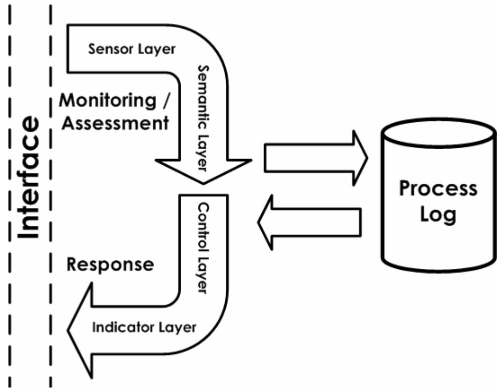

Fig. 2. Layers for context-aware information processing

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 [13]. The definition of how the data from one or more sensors has to be transformed is called an *aggregator* [14]. These rules are 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* [13]. 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 human readable. The active strategy of the control layer selects these representations and provides the aggregated information to them.

The first two layers are also considered as *interaction assessment* [7] or *user modelling* [27]. This suggests the integration of the sensor and semantic layer, although they expose different feature sets: The sensor layer is concerned with data collection of "low level information […] including, for example, key strokes, task initiation and completion, answers of quizzes etc." [7]. Its main objective is to organise incoming interaction footprints for further processing. In contrast, the semantic layer enriches , clusters, or transforms the data.

The last two layers are mentioned in the literature as *adaptation decision making* [7]. The control and indicator layer are commonly integrated as part of the user interface [2, 6, 11, 28, 29]. This is not always desirable because different combinations of strategies and indicators have varying effects on the learning processes and outcomes [42].

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, 9, 10, 11, 20, 44]. In contrast, our approach of smart indicators adapts the strategies on the control layer in order meet the changing needs of a learner. This allows providing different adaptation strategies for different phases of the learning process.

A prototype for smart indicators

In order to develop better understanding of supporting strategies of the learning interaction cycle we implemented a web-based prototype of smart indicators. The prototype integrates smart indicators into a community system. This system combines learner web-logs with del.icio.us[1] link lists and tag clouds of the community members. 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 the community.

[1] http://del.icio.us

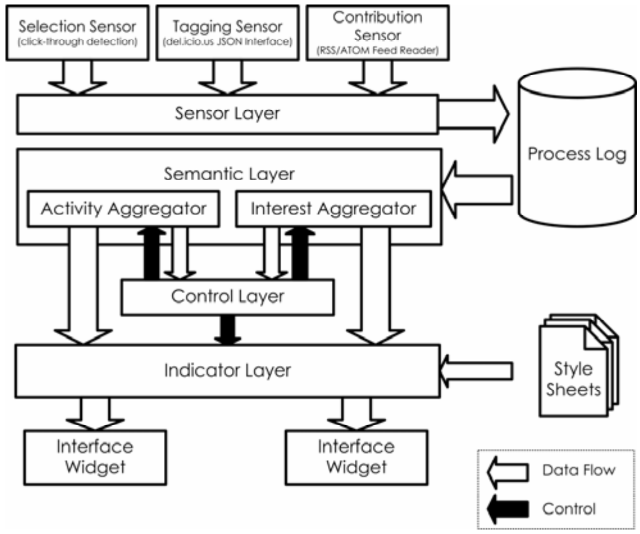

Fig. 3. Component interaction of the prototype

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.

Sensor Layer

The sensor layer captures sensor information on contributions, tagging activities and selections. This layer gathers and organises the interaction footprints of a learner in the community system. The prototype implements this by immediate and delayed interaction tracing. Immediate interaction tracing 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 activity on the user interface. Information on the collected links and comments for the community is gathered through del.icio.us' RPC interface[4]. The tagging activities are extracted from the data on tag clouds that is provided from both the link lists and the learner's web-logs. A learner tags a link or a web-log entry if a tag is added to the contribution. The data collected by the different sensors is stored in a central process-log for further processing.

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

The prototype uses six sensors to monitor the actions and interest of the community members:

1. *Tagging sensor*, which traces the tags that a learner applied either to a link in del.icio.us or to an entry in a web-log.
2. *Tag selection sensor* traces those tags that were selected from a tag cloud or a tag list of an entry in a web-log.
3. *Tag tracing sensor*, this sensor traces the tags that are assigned to web-log entries or del.icio.us links when a learner visits this entry.
4. *Entry selection sensor* that reports the hyperlinks a learner has accessed.
5. *Entry contribution sensor*, which traces the contributions of a learner to the community.
6. *Access time sensor*, this sensor traces the time of an interaction.

Semantic Layer

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 activity aggregator selects the data from the *entry contribution sensor*, *entry selection sensor, tag selection sensor*, the *tagging sensor*, and the *access time sensor*. Activity is defined as the number of actions per time interval. The activity aggregator calculates the activity for a time period for a learner or for the entire community. Additionally, the activity aggregator provides absolute or relative activity values. The absolute activity value is the total number of a learner's activities in a time interval. The relative activity value is defined by the relation of the absolute activity values of a learner or the community and the best performing community member. Both activity values are provided as a number.

The activity aggregator respects that the sensors do not contribute in the same way to the results with regard to effort, frequency and relevance. The aggregator rates contributions much higher than selections by adding a bias to the contribution activities. For example, selecting a hyperlink requires less effort than tagging some information, which requires less effort that contributing a new web-log entry or commenting a link in del.icio.us. It is also less likely that a learner tags a web-page or a web-log entry that has been already tagged by another learner. Thus, selections are likely to occur more frequently than tagging activities or contributions.

The interest aggregator selects data from the *tagging sensor*, *tag selection sensor, tag tracing sensor*, and e*ntry contribution sensor*. Interest is defined as the number of actions that relate to a tag. In other words, the more actions of a learner are related to a tag, the higher is the interest in it.

Claypool and colleagues identified that different types of sensors have varying relevance for identifying the learners' interest [12]. They distinguish between explicit and implicit interest sensors. Learners show explicit interest in a topic, if they select a tag from a tag cloud, label a link using a certain tag, or contribute a web-log entry on the topic. Implicit interest is given if learners follow hyperlinks that are tagged, or visit web-log entries that are related to a topic.

In this context, entry contributions, tagging actions and tag selections are explicit interest sensors while tag tracing sensors and entry selection sensors are implicit interest sensors. For the interest value, explicit sensor data is of higher relevance and has therefore a greater impact on the results of the aggregator. The interest aggregator reflects this by adding a bias to the values of the implicit interest sensors. This aggregator calculates for each tag in the tag cloud the interest value, and provides a data-set of tags and interest values as a result.

The interest value provides information about the kind of interest a learner has in a topic. For the prototype we distinguished between passive and active interest. Learners show passive interest in a topic if they access or tag information. Active interest is given if learners contribute comments items of the link list and through the web-log entries. The interest aggregator indicates this information by signed interest values. A positive value identifies those topics that are of active interest, while negative values show a learner's passive interest.

Control Layer

The control layer defines how the indicators adapt to the learner behaviour. The prototype implements two elemental 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 typical activity for learners who are new to a community is to explore the environment in order to develop knowledge about the community's interests, activities and participants. Hence, it is unlikely that learners start contributing actively to the community from the very beginning. During this phase the smart indicator shows only the absolute activity values in an activity chart and the raw tag list of the community (see **Fig. 4**). With each selection of a link or a web-log entry the learner's activity status grows and indicates that each activity has its value. The community's tags are shown as a plain list of tags. This gives the learners the opportunity to explore and to understand the different topics and relate themselves to the community's interests, without receiving suggestions on the most relevant tags in the community so far.

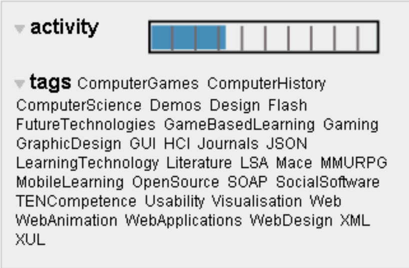


Fig. 4. Indicator of the first level strategy

Once a learner starts contributing links or web-log entries to the community, the control strategy selects relative activity values from the activity aggregator (see **Fig. 5**). The information displays the activity of the learner and the community for the last seven days as well as for the previous seven days. This adds a competitive element to the indicator: Learners see their activity in relation to the average community member and the best performing one. Additionally, it allows the learners to assess the changes of their activity levels from one week to the other. For motivational reasons, this is not applied before a learner starts contributing, because contributions have a greater impact on the average activity value than selection activities have. Therefore, it is difficult for non-contributing community members to reach the average activity level, whereas the bias on the contributions allows contributing members to reach activity levels above the average level more easily.

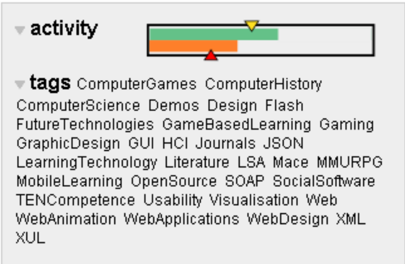


Fig. 5. Indicator of the second level strategy

After 10 web-log entries, the tag cloud starts to display the learner's active and passive interests in the tag cloud (see **Fig. 6**). A large number of contributions mark the end of the exploration phase. From this point in time trends of a learner's interest in different topics become assessable. Therefore, the third level control strategy uses the activity aggregator as well as the interest aggregator. By showing the interest in the different topics to the learners, they are enabled to identify the most beneficial topics of the community for their own learning process. This stimulates the awareness on concepts and their relations to the community activities.

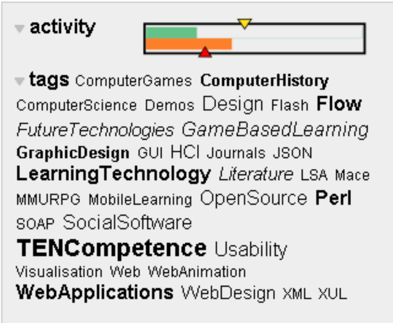


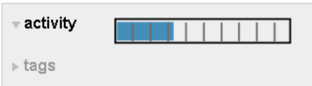
Fig. 6. Indicator of the third level strategy

Indicator Layer

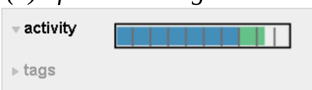
The main purpose of the indicator layer is to integrate the values selected by the control layer into the user interface of the community system. The indicator layer provides different styles of displaying and selects an appropriate style for the incoming information. To display information, the indicator layer of the prototype uses style-sheets to transform the data provided by the control layer into a learner accessible form. Depending on the style sheet the indicator layer generates an image or a widget.

For the prototype two graphical indicators and one widget indicator are defined. One graphical indicator is used during the first level of the control strategy. This indicator shows the amount of activities for the last seven days. The indicator has ten scales. Kreijns [28] suggests using logarithmic scales to give early steps a greater visual impact. We adopted this idea for the last three scales of the activity indicator: The first seven scales represent each three item accesses; the eighth scale represents 21 item accesses, the ninth 50 accesses, and the last scale represents 200 accesses. This assures a high visible impact of early interactions, while the activity bar is difficult to fill by active learners as **Fig. 7** shows.

(a) after accessing three items



(b) after accessing ten items

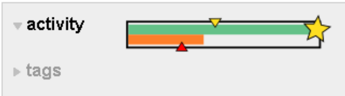


(c) after accessing 60 items

Fig. 7. Different stages of the initial activity indicator

The 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 (see **Fig. 8** a). The upper bar indicates the relative activity of the learner for the last seven days. The lower bar indicates the activity of the average community member during the same time period. Additionally, the indicator has two arrows. The upper arrow indicates the learner's activity for the previous seven days, whereas the lower arrow indicates the average community activity during that time. If a learner is the most active community member, a star is added to the end of the activity chart (see **Fig. 8** b).

(a) learner is less active than the community and less active than last week



(b) Most active community member

Fig. 8. Different activity visualisations of contributing community members

At the third level of the control strategy, 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 as the bigger font sizes of the related tags. For those tags that were of passive interest, the tag is set in italics. **Fig. 6** shows a tag cloud for an active learner.

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. The prototype showed the feasibility of implementing the architecture for smart indicators in a non-formal learning environment. Currently, we evaluate the validity of the educational approach and the adaptation strategy as it has been defined on the prototype's control layer. The evaluation is conducted in a small community of PhD students. Although the research is still in an early phase, we look forward to present the concept of smart indicators together with the first results of the evaluation.

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