# Learning Analytics: From Theory to Practice – Data Support for Learning and Teaching

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**Abstract.** Much has been written lately about the potential of Learning Analytics for improving learning and teaching. Nevertheless, most of the contributions to date are concentrating on the abstract theoretical or algorithmic level, or, deal with academic efficiencies like teachers' grading habits. This paper wants to focus on the value that Learning Analytics brings to pedagogic interventions and feedback for reflection. We first analyse what Learning Analytics has to offer in this respect, and, then, present a practical use case of applied Learning Analytics for didactic support in primary school Arithmetic.

**Keywords:** Learning Analytics, teacher feedback, didactic intervention, primary school, formal education.

## 1 Introduction

The idea of Learning Analytics has emerged in recent years as an educational way of utilising the enormous amount of learner data produced through activities in electronic systems. Already back in 2006, Retalis et al. (2006) considered interaction analysis a promising way to better understand learner behaviour. However, only the more recent explosion of data and increased utilisation of user data in business and commerce have brought this domain to the full attention of the education sector (Horizon 2011).

Since the Horizon report came out, there has been massive interest and research activity happening in this new domain. Researchers started busily engaging in diverse debates to define and scope Learning Analytics and to contrast it with existing areas of research like educational data mining (EDM). A number of descriptive models and frameworks have been proposed to capture the extent and implications of the research area (cf. Siemens 2011, Elias 2011, Greller & Drachsler 2012, Cooper 2012, Chatti et al. 2012, Friesen 2013).

Because analytics in education are not confined to teaching and learning alone, there were moves to separate the semantics into "unrelated" sister-domains such as Academic Analytics (Siemens 2011). The latter is closely related to business intelligence in that it works more towards efficiency of operations than towards the support for progression in learning (cf. Van Harmelen & Workman 2012). In the same vein, Research Analytics, which relies heavily on bibliometric data and citation indexes,

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due to its direct connection to institutional funding mechanisms, can be excluded from the spheres of Learning Analytics in the pedagogic sense.

When scanning the literature on Learning Analytics, we find a heavy slant towards the processing (EDM) side of things with research discussing algorithmic approaches to learner data. Similarly, the institutional data governance and acceptance aspects have played an important part in the evolution of Learning Analytics as a research topic (cf. Graf et al. 2012; Ali et al. 2013). By contrast, the use of analytics as a support tool for teacher interventions is an area with relatively little coverage to date. However, to exploit analytics as an instrument for reflecting current pedagogic practice and for validating didactical patterns, as indicated by Greller & Drachsler (2012), more attention to this aspect is required. In this paper, we want to elaborate on the embedding of analytics approaches into teaching and learning, on how questions can be raised about didactical methods informed by analytics, and where analytics can provide new insights to the preparation of cognitively difficult areas of learning.

This paper is structured in the following way: In Part II, we talk about Learning Analytics and its place in pedagogy. This is then followed in Part III by introducing a practical application of an analytics tool for monitoring the development of children's Maths skills in primary school. Part IV discusses the outcomes of this experiment and the value potential of Learning Analytics. Finally, in Part V, some lessons learnt and conclusions are drawn and prospective research question raised.

## 2 Pedagogy and Learning Analytics

The relationship between pedagogy and Learning Analytics is understood differently within the community and with respect to everyday practice. Some researchers see Learning Analytics as intrinsically pedagogic in its nature, just by dealing with educational data or with data usable for learning in the widest sense. Feedback systems play an important part in this. Among other examples, Duval (2011) claims that, "a visualisation of eating habits can help to lead a healthier life". In his elaboration it seems, that learning happens by mere visualization of data, though Duval too asks for more orientation towards specific goals. The EDUCAUSE summative report (2012) of a three day online seminar stresses the importance of any analytics program to derive meaningful, actionable insights. We consider the word 'actionable' as being critical for the exploitation of analytics results in teaching and learning.

In our elaborations here we will use a narrower setting of pedagogic application, relating directly to formal education in the classroom. We also follow the model by Greller & Drachsler (2012) who keep pedagogy and data analysis strictly separate, using Learning Analytics as an instrument to reflect upon and to take informed decisions on learning interventions by a human agent. This stands to some extent in contrast with predictive approaches of Learning Analytics, where decisions on follow-up actions can be based directly on the data through automated algorithms.

Greller & Drachsler (ibid.) position Learning Analytics between brackets of pedagogically induced behaviour and the interventions actioned either by a teacher or the learners themselves (Fig.1.). These interventions may lead to changes in pedagogic behaviour (learning activities) that, in turn, (re-)inform the Learning Analytics process for measuring progress against the intended learning outcome (Van Harmelen & Workman, 2012).

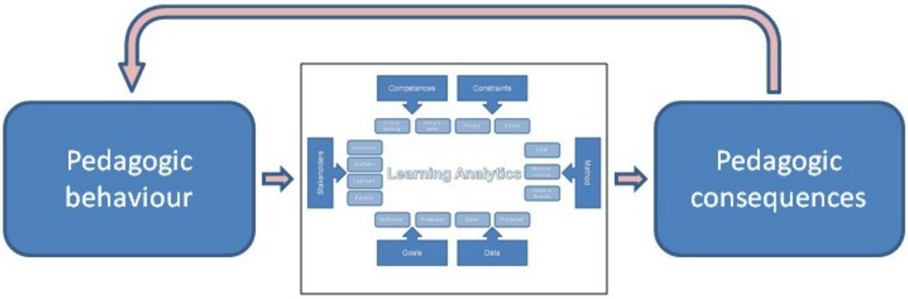


**Fig. 1.** Learning Analytics embedded in pedagogy (Greller & Drachsler 2012)

One of the strengths of Learning Analytics as a support for teaching and learning is the potential to bring to light insights that would otherwise not be easily visible. Learning Analytics can help backing up "feelings" with data. On the other hand, it may also lead to refuting "general assumptions" about students' behaviour in specific learning actions. On a larger scale, this may lead to rethinking the educational process and pedagogic approach in certain areas of teaching. To illustrate this potential, we will introduce a small application that analyses the performance of primary school children in learning the tables.

## 3 A Primary School Analytics Application

Graz University of Technology has a long tradition in doing technology enhanced learning (TEL) both in research as well as in academic programmes with a special focus on students and their learning (Ebner et al. 2006). Longitudinal studies pointed out that any student of today now owns an arbitrary amount of different technologies – a Personal Computer, a laptop, a smartphone, maybe also a tablet or an eReader (Ebner et al. 2013; Ebner et al. 2011). In combination with a mobile broadband Internet connection it is save to state that practically everyone has access to information and communication in real time, even while on the move. On the other hand, modern web technologies also allow us to develop innovative information systems that are able to store huge amounts of data. The general idea with respect to education is to enable learners to utilize their personal (mobile) devices to exercise and improve on predefined learning tasks.

Bearing this generic vision in mind, different applications have been developed to gather learner data, interpret and visualise them as they work in these seamless learning environments. Afterwards, a teacher is able to bring the results back to the classroom for reflection and deep learning. In our particular case, three applications have been produced: (1) the *Multiplication Table* (Schön et al. 2012), (2) the *Multi-Math-Coach* (Ebner et al. 2014a), and, (3) the *Addition / Subtraction Trainer* (Ebner et al. 2014b). All of these applications address core maths operations for school children in primary schools. Each application consistently observes the following rules:

1. School children train or play with the application (e.g. web interface or special mobile apps) as often as they want.
2. Each single calculation is stored in a centralised database on a webserver.
3. The entered data is checked for correctness and the current competence level of a child is calculated. Based on this, the next calculation will be chosen.
4. The teacher gets an overview how their class performs as a whole or each child individually. In case of occurring problems, a visualisation prompts the teacher to a pedagogical intervention.
5. To avoid chance successes, each answer has to be entered correctly twice to be accepted as accomplished.


**Fig. 2.** The Multiplication Trainer (http://mathe.tugraz.at)

Fig.2. shows the main graphic interface of the trainer application that helps pupils learn the 10x10 table. In the middle of it, the current calculation is shown and the answer is expected in the input field during the given time frame (bar running down to time-out). On the left side, an overview of all questions already completed is given. Below the task, a little rabbit should help motivate children doing the next question in a playful manner (the rabbit advances on correct answers towards a carrot). Fig.3. illustrates the teacher's overview: In the first column on the left, the names of the children would appear and following the alignment each single calculation is displayed. Dark green means the particular example has been mastered well by the child, lime green indicates that it is known and red is not known (grey just means that this calculation has not occurred yet). Much more important is the second column from the left called "skill". Here, the application predicts the current learning state in a traffic light metaphor. A yellow or even red box prompts the teacher that a pedagogical intervention is recommended.

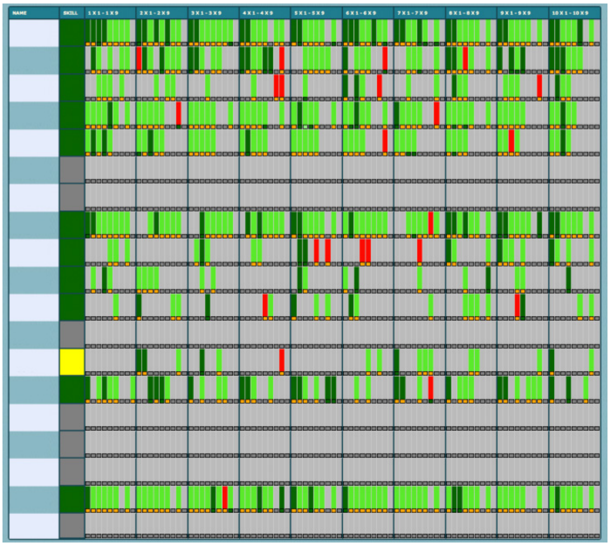


**Fig. 3.** Teacher's overview

The application, therefore, simultaneously takes a training and assessment perspective. Children can practice the table, but are at the same time measured for correctness and progress. The time taken to answer is also a factor taken into account as an indicator for the level of competence. Although this is a very simplistic case, a number of insights can be deduced from it as we will discuss in the next section.

The analysis of the performance of individual children should, as depicted in the model above (Fig.1.), lead to pedagogic interventions. Rather than waiting for the children learners to complete the table tests, early warning can already alert the teacher to struggling pupils. We will here not express any opinion of what the "correct" intervention would be in each individual child's case, but assume that teachers adopt further interpersonal diagnostics to find out in which way a child is struggling and how to help them. After they have been brought back on track, the cycle of testing can start again.

## 4 Findings and Discussion

From our test run with about 6,000 pupils at the ages of 7-10, and more than 100 teachers, it clearly emerges that Learning Analytics is more than just collecting, curating and processing data. As indicated in chapter II above, Learning Analytics is about the interpretation of data to actively assist teachers with meaningful and actionable figures or visualisations. In other words, the data itself is not enough to advance learning, because the pedagogical approach must be looked at in its entirety. For this to happen, we find it among other things important that teachers see the performance of each individual learner. Teaching and learning, despite the constraints posed by large cohorts in search for more economic efficiency, from the learner perspective still remains a one-to-one relationship to personalise the pedagogic approach and support the individual in their psychological, mental, and physical development. However, in group situations like a classroom, it is difficult for a teacher to keep an eye on the progression of each child or to surface collective issues that have perhaps not been properly addressed through the chosen delivery method (cf. Drachsler & Greller 2012).

In our little maths application, feedback to the teacher is continuous and formative. The mentioned box indicators are early warning signals should any child begin to struggle with progress on the table. A teacher has the possibility of monitoring the entire class and may intervene when warning signs occur. The timeliness of the feedback to the teacher is perhaps the biggest added value that Learning Analytics brings to teaching practice.

In monitoring the activities of each child in real time, analysing the performance and predicting the likely progression helps the teacher to identify outliers early. Children struggling with certain calculations are timed out by the game. This time-to-response counts towards the prediction algorithm. One interesting finding from the application is the likelihood of success and failure, as well as emerging patterns, which allow approximations of a child's performance. For example, the observation implies that pupils who run into a performance of right-wrong-right-wrong would never come out of this loop switching between correct and incorrect answers for the same given questions (Taraghi et al. 2014). Similarly, when a child answers two consecutive questions wrong, there is a 30% probability that the next two will also be wrong.

A summative analysis across all participants also has interesting things to tell. It highlights where the most difficult items of the multiplication table lie (Fig.4. below). 8*6 as well as 6*8, followed by 7*8, have to be considered as the most difficult questions according to the data evidence. This cumulative knowledge over the entire learner population should be used by teachers to adjust teaching plans and put perhaps more focus on the exercises of difficult areas. In this way, Learning Analytics brings information to light that would otherwise be difficult to spot or to articulate with evidence.

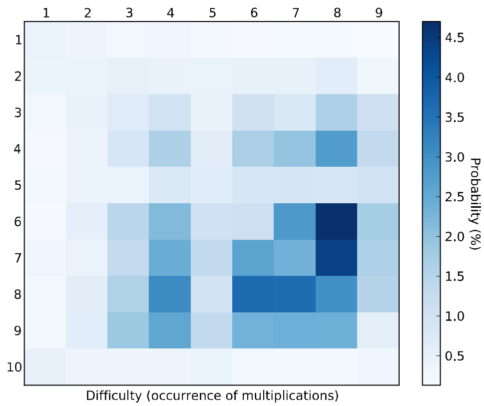


**Fig. 4.** Heat Map of the most difficult questions

From these findings, we can take a matrix approach to interpreting the data in the application with two main pedagogic intervention paths to follow: The horizontal analysis shows the performance of each child along the posed tasks. Vertically, the summative group analysis can be performed with views on the individual posited tasks and the relative cognitive challenge they pose to the learners. While the horizontal axis may lead to personalised intervention and support, the vertical axis provides food for curriculum adjustments to cover more challenging areas with greater teaching efforts. The predictive warning signals of possible difficulties a child experiences provides added support for timely focussing teacher attention where it is needed.

## 5 Conclusions and Future Research Questions

One of the results of our tests is that Learning Analytics must be easy. The practical experiments pointed out clearly: – teachers have no time to interpret data in detail, due to the fact that in the classroom they have to observe and react to many different events at once. This has already been pointed out as a risk in previous works (Van Harmelen & Workman 2012). In our case, traffic light signalling was chosen to quickly provide the appropriate hint. It goes without saying that the prediction algorithm running in the background must be carefully tested and tuned, and has to be adapted if necessary.

From the learner perspective, Learning Analytics helps the individualisation of the learning process: The strength of interpreting data of a single learner is that we exactly know about their learning problems. Therefore, pedagogic help can be provided in a very personal way. On an ethical note, though, we have to concede that Learning Analytics is about data, and one of the major concerns of this emerging field is how the collected data is protected against abuse. First studies on this topic point out that teachers as well as researchers have to address this topic with great sensitivity (Kay, 2012). However, it is our opinion that in a protected classroom environment (whether a physical or virtual environment), it is absolutely essential for the holistic pedagogic development of a child that teachers have direct access to personal information relating to their pupils learning.

As a matter for future research, we consider our trial limited in the way of covering a well-defined and limited space of maths education. Confirmation of Learning Analytics support for pedagogic interventions from more complex and abstract areas would be highly relevant for unleashing the fuller potential of Learning Analytics. Among other aspects, the psychometric conditions of children, who come at different levels of preparedness could be studied against the mastery of the table questions. Repeat runs with the same pupils could potentially highlight the changing conditions of the test parameters and difficulty level (cf. Item Response Theory, Thomsen 2009).

Furthermore, there have been some attempts to "socialise" Learning Analytics (e.g. Buckingham-Shum & Ferguson 2012) and to apply it to open education spaces like learning networks and MOOCs (Fournier 2011). Free analytics tools like SNAPP provide first interesting results, but, at present, they still remain rather specialist tools that are hard to grasp for teachers and are difficult to build into reflection and learning design of everyday teaching. However, this is an interesting space to watch not only with respect to supporting open learning with Learning Analytics, but also to bring social aspects of analytics into the classroom. In future studies, we, therefore, aim to look into experiments with social character such as group work or social network analysis (SNA).

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