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Learning Analytics Artefacts in a Cloud-based Environment: a Design science perspective

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Abstract: Learning analytics is the analysis of learning data for optimising learning and learning environments. A number of models or frameworks for learning analytics have been proposed, which focus on the process of analytics. Motivated by framework developments in other areas, such as systems development and IT management we propose to view learning analytics through the lens of design science. We identify a set of artefacts which extend the existing learning analytics framework along a second dimension. Incorporating a learning model based on interaction theory, the extended framework and artefacts are applied to a case study of business computing students studying customer relationship management in a cloud computing environment. The study shows the artefacts to be useful in extending the descriptive ability of the analytics framework.

The significance of the work is that it provides a view of analytics through the lens of design science. In this way the extended framework provides a number of advantages for the application of learning analytics. The framework also contributes to learning analytics research by expanding the analytics vocabulary and providing tools for further research.

Keywords: learning analytics, business intelligence, cloud computing, design science

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1 Introduction

Business Analytics is the practice of iterative, methodical exploration of an organization's data to support data-driven decision making (Barneveld, Arnold et al. 2012). Academic analytics is the application of this practice to education, responding to the reporting and decision making challenges facing academic leaders and managers (Oblinger and Campbell 2007). At the operational level of teaching and learning this can be applied as learning analytics, "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs" (SoLAR 2012).

Analytics is a process or methodology as well as a set of technologies. A number of models or frameworks for learning analytics have been proposed (Elias 2011). However, these frameworks are focussed on a single dimension of analytics: process. Frameworks in other similar problem domains are generally multi-dimensional, providing a number of different perspectives on a problem. Furthermore, analytical approaches are generally most successful when based on a clear model of the underlying problem domain. In education, E-learning theory describes a model of student learning, in which student activity and student interactions (with content and environment) are the primary drivers of learning.

Cloud computing services provide a novel information technology environment and are being widely deployed in education. Using the cloud, educators can now deploy sophisticated business applications such as SalesForce.com in the classroom, providing students with an immersive, real-life, active learning experience. Like the standard VLEs (such as Moodle), these systems offer an environment in which the user is immersed and user activity is extensively recorded. Furthermore, SalesForce, like many cloud systems, provides tools for accessing the database underlying the applications and for creating custom applications. This combination of rich data and technology tools presents an unique opportunity for the application of learning analytics.

The problem with current approaches is that they view learning analytics either from a technical point of view or a one-dimensional process view. In order to address this problem we apply a design science lens to investigate artefacts in Learning Analytics. In this paper, we introduce a set of learning analytics artefacts which modify existing Learning Analytics frameworks along a second dimension. The artefacts are designed using a design science approach and incorporating a learner interaction model. The artefacts are instantiated in a case study of computing students studying enterprise cloud computing. The main contribution of the paper is providing the set of artefacts and a modified framework that can assist researchers and practitioners to design, compare and validate learning analytics systems.

The remainder of the paper is structured as follows. In section two, we describe existing learning analytics frameworks. Following that we propose in section three a set of artefacts that modify the framework and relate the analytics framework to a learning model. Combining the modified analytics framework and the learning model, in section four we use a case study to examine the framework, followed by our conclusions.

2 Related Work

2.1 Learning Analytics

An increasingly complex environment, a vast proliferation of data, and greater competition, has forced organisations to use information technologies as a platform for a more analytical approach to management and decision making (Hopkins, Kruschwitz et al. 2010). Variously described as business intelligence, business analytics, or data mining and knowledge discovery, this approach has become a major trend in the application of information technologies to organisational management (Hostmann, Rayner et al. 2006).

Within educational technology, there has been a recent expansion of analytical approaches such as educational data mining (Romero and Ventura 2010) and academic analytics (Barneveld, Arnold et al. 2012). However, much of the analytics research has been at the institutional level (Hopkins, Kruschwitz et al. 2010), (Oblinger and Campbell 2007), rather than the level of individual learners and educators and these approaches have not as yet been widely applied to cloud-based environments. Furthermore, the analytics approaches tested so far have tended to focus on technical aspects of analytics and have been insufficiently integrated with the practice of teaching and learning or with the wider field of educational technology research (Baker and Yacef 2009), (Murnion and Helfert 2011). Experience in applications of analytics has indicated that analytics is most successful when applied using a framework or model that guides the analytics process and relates that process to the underlying problem domain (Shearer 2000).

2.2 Analytics frameworks and methodologies

A number of models for business analytics have been described: (Shearer 2000), (Hostmann, Rayner et al. 2006), (Oblinger and Campbell 2007), (Hopkins, Kruschwitz et al. 2010), (Elias 2011), Selecting the more recent analytics models that describe the process of analytics, it is clear that they share a number of common elements, as shown in table 1 below.

Analytics Model (Oblinger and Campbell 2007)	**IBM Analytics Model** (Hopkins, Kruschwitz et al. 2010)	**Learning Analytics Model** (Elias 2011)
1. Capture	1. Define	1. Select & Capture
2. Report	2. Capture	2. Aggregate & Report
3. Predict	3. Aggregate	3. Predict
4. Act/Share	4. Analyze	4. Use
5. Refine	5. Disseminate	5. Refine
		6. Share

Table 1: Analytics Models and Elements

From the above sample it can be seen that there is general agreement on the required elements of an analytics process. These can be summarised as: capture & organise, aggregate & report, predict, act/share, and refine.

Capture & Organise
Data is the basis of all analytics techniques. However, the definition of the data to captured can be problematic (Hopkins, Kruschwitz et al. 2010), (Elias 2011). The data can be required from multiple different sources (Oblinger and Campbell 2007) and must be captured, organised and stored using appropriate data management or data warehousing tools (Hoffer, Prescott et al. 2007). Too often, this process can consume too much of the analytics effort (Hopkins, Kruschwitz et al. 2010).

Aggregate & Report
The organised data can be summarised and aggregated into reports containing descriptive, meaningful information, although text-based reports are increasingly being replaced by graphical dashboards and complex visualisation methods (Mazza and Milani 2004). Reporting involves decisions about key metrics to be measured and displayed (Rogers, McEwen et al. 2010) and the deployment of query and descriptive statistics tools (Oblinger and Campbell 2007)

Predict
The aggregated data can be analyzed using statistical methods. Key factors in the success if this process are the effectiveness of the predictive models selected and the skills of the analytics team (Oblinger and Campbell 2007). A typical application in learning analytics is predicting final student grades from course data (Macfadyen and Dawson 2010). Prediction is usually based on statistical algorithms such as regression models. Timing and frequency of model operations depends on the problem being solved (Oblinger and Campbell 2007).

Act/Share
A key feature of successful analytics is ensuring that the analysis is actionable (Norris, Baer et al. 2008). Action can range across a spectrum from simple information provision for decision makers to triggers to educational interventions (Oblinger and Campbell 2007). In many cases, the action can be

to share the knowledge created in a collaborative decision making environment (Dron and Anderson 2009).

Refine
Analytics approaches should include a self-improvement process, periodically amending models and methods (Oblinger and Campbell 2007), returning results of the analysis in a feedback loop improving the learning system (Romero and Ventura 2007), and at its best, embedding the results of analytics into the decision making processes (Hopkins, Kruschwitz et al. 2010).

However, despite the general consensus on elements of the analytics framework, it is quite sparse in that only one dimension is described: the set of methods (a process dimension). Analytics is both a methodology and a complex technical process. Other information systems-based methodologies and processes of similar scale have been described from multiple different perspectives. For example, the development process for large information systems, the Systems Development Life Cycle (SDLC) has been described from a multitude of perspectives or dimensions; from phases and processes to models and structures (Whitten, Bentley et al. 1998). Similarly, the management of IT systems in organisations has been described by frameworks which are multi-dimensional such as the Zachman framework (Zachman 1987) and the IT-CMF framework (Curley 2009).

This approach, of describing a set of dimensions for a framework, requires a design methodology. One such methodology is Design science, a research methodology that aims to use the design of artefacts (which may be frameworks, models, or methods) as the central component of research (Carcary 2011). In order to investigate artefacts of learning analytics, we employ a design science perspective.

3 Design Science and Framework Development

Design science is a research methodology that is centred on the production of artefacts that can be evaluated for practical utility and for contribution to theory (Hevner, March et al. 2004). Design science takes as its fundamental building blocks four types of artefacts (March and Smith 1995). **Constructs** are concepts which form the vocabulary of the research problem. **Methods** are steps (or guidelines) used to complete a task, and based on the underlying constructs. **Models** are representations of the problems area, describing how things are. **Instantiations** are the realisation of an artefact in its environment. For this study design science provides a lens with which to view the problem of learning analytics frameworks and a vocabulary to describe the process of framework development.

Based on this understanding, the first requirement is identification of a common vocabulary; in design science terms the requisite *constructs*. Several descriptions of analytics approaches have referred to the concept of the knowledge continuum (Elias 2011), (Romero and Ventura 2007), (Murnion and Lally 2009), in which data at the bottom of the continuum is converted into information, then knowledge and then wisdom. The continuum is often depicted as a knowledge pyramid (Ackoff 1989). In her examination of analytics frameworks, Elias (2011) matched the elements of the knowledge continuum to the processes of analytics.

Table 2: Knowledge Continuum of Analytics (Elias 2011)

Knowledge Continuum (Constructs)		**Steps of Analytics (Methods)**
Data	Obtain Raw Facts	Capture
Information	Give Meaning to Obtained Data	Report
Knowledge	Analyze and Synthesize Derived Information	Predict
Wisdom	Use Knowledge to Establish and Achieve Goals	Act
		Refine

Given a set of *constructs* which form the basis of the analytics framework and a set of *methods* for progressing through the framework, we propose another perspective on analytics (in the vocabulary of Design Science, a set of artefacts) which is a set of *models* providing representations of the analytics problem for each method.

3.1 Proposed Analytics Artefacts

Based on the fundamental construct, the knowledge continuum, we propose and describe new artefacts, specifically analytics models, one for each analytics method.

Table 3: Analytics Artefacts

Methods	**Models (Artefacts)**
Capture	Data model
Report	Information model
Predict	Predictive model
Act	Decision model
Refine	Analytics model

Data model
A data model provides a representation of the existing data in the source data system(s). These can be described using standard database models (such as entity-relationship diagram models)

Information model
Describes the information for reports, including simple aggregation functions such as Sum() and Count() and more complex models such as cross-tabulations. In addition to describing the precise content and structure of the information an information model could also include descriptions of the type of information required. An example would be information quality metrics such as timeliness, accuracy, and completeness (Alkhattabi, Neagu et al. 2010).

Predictive Model
There are libraries of standard predictive models (regression, classification, association, etc.). However the analytics prediction model might incorporate further factors such as model reliability and timing of model runs (Oblinger and Campbell 2007).

Decision Model
A decision model can be as simple as directing relevant information to appropriate decision makers at the right time i.e. a reporting rules system, in contrast to the information model which deals with the content of reports. A more complex decision model could trigger actions based on a rule-base consisting of a set of IF ... THEN rules or a formal decision tree. However production rules and decision trees are mostly suited to highly structured, routine decisions. More sophisticated decision models could incorporate elements of the decision making process such as support for collaborative decision making.

Analytics model
For analytics to improve (Refine method), the analytics methods themselves must be modelled within the system. This meta-model could be as simple as the set of the other four models plus model management meta-data e.g. model creation data, model execution data, user comments, etc. However if the Refine method is to impact on the underlying learning (rather than only on the analytics) the analytics model should include a model of the learning context.

Using Design science as a lens to view the problem, we have amended the existing framework by adding new artefacts, a set of models. The fourth artefact type in design science, *instantiation*, refers to the realisation of the other artefacts in their environment. In order to do this it is necessary to relate each artefact to the underlying domain of teaching and learning. That requires another construct: a learning model.

3.2 Learning Model and Interaction

In order for analytics to be effective, an understanding of the domain to be analysed is required, whether that is to generate a problem definition (Shearer 2000), provide a basis for the general design of the analytics system (Pahl 2006), or to determine the precise data that needs to be captured for analysis (Oblinger and Campbell 2007). One way to understand this domain is to use an accepted learning model.

One of the central features of learning is learner interaction (Anderson 2008), (Ohl 2001). Interaction can be of three types: learner - content, learner - interface and learner – support (Moore 1989). Computer-based learning environments which simulate a real-life system can provide a particularly effective learner – content interaction (Ohl 2001). These kinds of learning environments support activity based learning, the acquisition of knowledge by actions, or operations (Ohl 2001). Learner activities, such as application and practice, generate interactions with learning content, which in return generate new activities (Ally 2008).

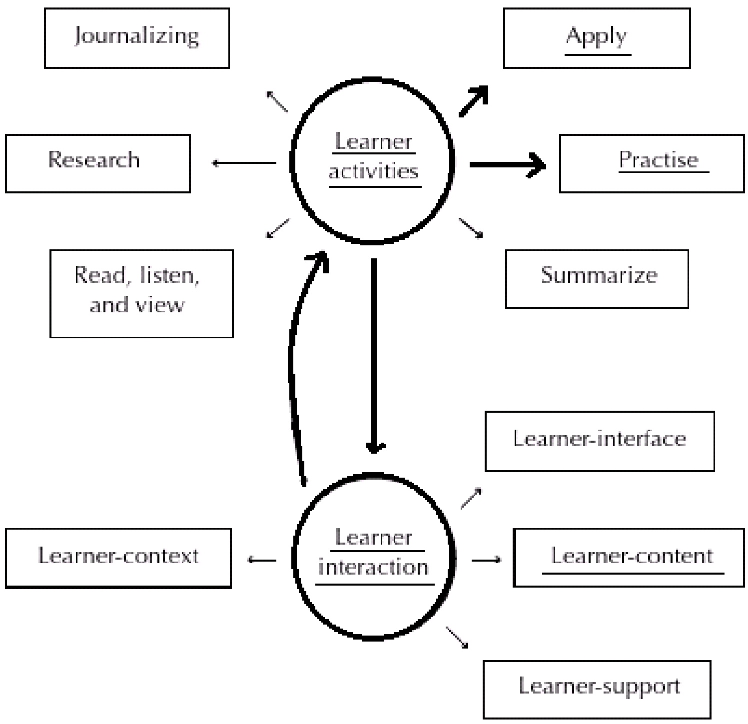

Figure 1: Learning Model (from (Ally 2008), our emphases)

Based on the model described above we propose that in a computer-based active learning environment **learner – content** interaction is critical and that this interaction, in an applied learning context, requires and causes continuous student activity in the form of **application** and **practice**.

However learner – content interaction is not simply a one-dimensional scalar variable, it is a multi-faceted concept (Anderson 2008). Much educational practice assumes this uni-dimensionality, for example counting student attendance. Several applications of analytics to online learning, similarly, use a count of student logins as a measure of student activity, such as the usage statistics in Moodle reports (www.moodle.org), or studies measuring LMS usage (Heathcote and Dawson 2005). However other researchers have defined measures of interaction which are qualitative (Janossy 2008) and multi-dimensional (Roblyer and Ekhaml 2000). The extensive field of educational data mining (EDM) is predicated on the principal that learner interactions, or learner behaviour, involves complex patterns amenable to data mining algorithmic approaches (Baker and Yacef 2009), (Romero and Ventura

2010). Thus, an understanding of learner activities and learner – content interactions provides not only the basis for the simplest artefact, the Data model, but also for the more complex artefacts such as the Information and Predictive models. In section 4 we combine this interaction-based learning model with our proposed analytics artefacts in a case study of learning analytics in a cloud computing environment.

4 The Case Study

4.1 The context: Cloud-based services for business computing education

The case study is based on the students in first year of a Business Computing degree. The students use a cloud computing system for customer relationship management (CRM).

Cloud computing is the provision of simple, on-demand access to pools of highly elastic computing resources as a service over the Internet, where the user need not be concerned about how it works it, or where it is located (Marks and Lozano 2010). Cloud computing can be divided into several service layers: The final layer; Software as a Service (SaaS), is what users and consumers of cloud computing interact with, when they access their Google docs or upload images to a photo sharing application online. With SaaS the user is getting a complete information system or application suite, but as a service, rather than as purchased software installed on a local machine. One of the most well-known and established SaaS providers is Salesforce.com, the "enterprise cloud computing company" (www.salesforce.com). Salesforce.com now offers a raft of cloud computing solutions, but it's original and most well-known service is the customer relationship management (CRM) service now called Sales Cloud but still known as Salesforce by the user community.

CRM is a set of business processes and related technologies for managing customer relationships to add value for customers and thereby the company (Chalmeta 2006). CRM technologies evolved from contact managers and sales force automation tools into complete systems that manage customer relationships in a single way and provide an integrated view of customers. As such, CRM is a central element of the marketing function (Kumar and Reinartz 2006). Business computing students using the Salesforce CRM system are thus able to interact with the customer life cycle (Berry and Linoff 2011) and are also exposed to enterprise-level cloud computing technology.

Using this technology, it is possible to create an effective learning environment for business computing students. In terms of the learning model from section 3.2, the emphasis is very much on Learner – Content interaction. Students are assigned typical tasks associated with the customer lifecycle: creating new Leads, converting Leads into Contacts and Accounts, and updating Opportunities. Because the system contains a central database, each student sees the activity of all the other students. At the same time, because Salesforce is designed to create a collaborative work environment, each piece of newly created data is assigned an owner, so each student can identify exactly what data belongs to them. As the students work through the customer lifecycle they continuously update the CRM database which provides a detailed source of student activity data for learning analytics. In the next section we describe examples of learning analytics artefacts derived during the case study.

4.2 Case/Implementation

The Business Computing students worked in the Salesforce CRM environment for part of a semester and were examined on Salesforce and CRM element at the end of that period. The data was extracted from Salesforce using the Force.com Explorer and the Salesforce Object Query Language (SOQL). The information modals were created and stored in a data warehouse created with Microsoft Access 2007 and further analytical models were constructed using the IBM SPSS Modeller suite.. In our complete case study we constructed a number of analytics scenarios, each of which described a complete instance of the Learning Analytics framework. However due to space constraints we present here only one scenario.

4.2.1 Scenario

In this scenario the objective of the analytics process is to examine a particular pattern of learner activity. In this learning context, which is activity-based and applied, application and practice are the key to learner – content interaction and thus effective learning. We assume that the total amount of interaction is less important than continuity of interaction. The analytical hypothesis is that a gap in activity will be detrimental to learning outcomes. Based on this analytical problem we can define the appropriate analytics artefacts.

Artefact	**Description**	**Example** (highly summarised for illustrative purposes)
Data model		
The required data is a count of specific activities, for each user, with a date stamp for each activity, from the Salesforce database. Also final student grades from the examiner. The two data sets are joined on student ID.		Activity data ID Activity Date 01 Create Lead 02/03 03 Create Lead 02/03 01 Create Lead 08/03 : : : Student grades ID Grade 01 67 02 36 : :
Information model		
The model groups activity data into time periods (weeks) by user. Activity in a time period is given a binary classification: 0 if zero learner activity, 1 if learner activity is greater than zero. Finally the number of non-zero time periods is counted. Final grades are converted into a binary Pass(1)/Fail(0) Grade		Activity Learner Wk1 Wk2 Wk3 Non-zeros 01 1 1 0 2 02 1 0 0 1 : : : : : 27 1 0 1 2 Student Grades ID Grade 01 1 02 2 : : :
Predictive model		
A Classification model is used. Learners are classified as Pass/Fail based on activity aggregate (non-zeros) in the information model		The model used was Chi-square. The results were statistically significant ($p = 0.047$) suggesting that gaps in student activity deserved some action
Decision model		
Timing of analysis is necessarily end of module since final grades were used. Decision rule can be to amend next run of module		Based on the findings of the predictive model a possible solution is to insert continuous assessment.
Analytics Process model		
The Salesforce setup includes a dashboard for the administrator (Tutor) showing raw student activity data. The predictive model provides greater analytical insight than this data.		Refine the system by adding the results of the information model (summarised) to the dashboard.

From the scenario described we can see the complete learning analytics framework in action including instances of each of the learning analytics artefacts, albeit in a highly summarised form. An important feature of artefacts in design science is that they are observable and measurable and thus contribute to the general theory or framework. This case shows how each artefact can be instantiated and described in concrete terms. In the next section we make some conclusions based on this work.

5 Conclusion and further research

Our framework extends existing analytics frameworks by viewing learning analytics through the lens of design science, which allows us to identify relevant artefacts. We introduced and described learning analytics artefacts in the form of a set of models that relate existing analytics methods to the underlying construct, the data-knowledge continuum. Based on the case study we were able to observe and describe the implementation of the extended framework and the new artefacts. The new framework makes a number of contributions. Existing analytics frameworks have been focussed on the process (methods) of moving up the knowledge continuum, from data to knowledge. The addition of the new artefacts provides a different, descriptive perspective, allowing analysts to check and describe exactly where they are on the knowledge continuum at any point in the process. Furthermore, these models by their nature consist of persistent data that can be stored and shared. Sharing can occur along the time dimension so that the goal of continuously improving and refining the analytics process can be more easily achieved. Sharing can also occur on the organisational dimension, where models developed in one analytics process can be shared and re-used in other parallel analytics attempts. The framework also attempts to address the perennial requirement of analytics to be connected to the underlying problem domain. The particular learning model used in our case might not be universally accepted but we expect that the process of relating knowledge artefacts in an analytics process to a learning model should always occur in an effective learning analytics approach. In addition to these advantages in the application of learning analytics we expect that our framework will make a contribution to learning analytics research. The artefacts we have described and instantiated are concrete, observable and measurable, expanding the vocabulary of learning analytics and providing tools for further research. Furthermore the paper contributes to Design science research by demonstrating how Design science can be employed to analyse a complex information technology application environment, such as learning analytics.

Based on this work we see a number of further research directions. The first is the possibility of identifying further artefact sets (dimensions) to be described and tested. We have extended the framework by adding a models dimension to the existing methods dimension. There could be other dimensions to analytics that require examination, for example a technology dimension, describing the Information technology tools and systems being used and connected to at each stage in the analytics process. Finally we identify a limitation in applying Design science to identify artefacts. So far we have only observed and structured the set of artefacts. In further research we aim to complete the design of these models

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