Cross-LAK 2016

the first international workshop on

Learning Analytics Across Physical and Digital Spaces.

This workshop is co-located with 6th International Conference on Learning Analytics & Knowledge (LAK’16), the top conference for which is taking place from April 25 to 29 in the University of Edinburgh, Scotland, UK

Preliminary Proceedings

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Profiling High-achieving Students for E-book-based Learning Analytics

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Abstract: The purpose of this paper is to mine or detect meaningful learning patterns for profiling high-achieving students using e-book-based activity logs and questionnaire. The analysis of this study uses association analysis with Apriori algorithm. Logs for this analysis were collected from 99 first-year students who use a document viewer system called BookLooper, questionnaires and Moodle in an information science course at Kyushu University. From the results of the association analysis, we found that high-achieving students and BookLooper have significant relationships in terms of preparation and review time. This paper believes that the profiling and analysis can be used to predict their final grades and to detect effective learning patterns.

Keywords: Learning analytics, e-book, data mining, association analysis, user profiling

Introduction
Nowadays, majority of textbooks are not only published in printed format but also are created as electronic textbook (e-book) format available online or on mobile devices. As a Japanese government policy, they plan to introduce e-books in all K12 schools by 2020 (MEXT). Many countries’ e-book policies only focus on introducing the technology of e-books into K12 schools (Fang et al., 2011), (Shin, 2012). However, little attention has been paid to analyze and mine important information for profiling from the e-book activity logs. Therefore, it is necessary to explore various analytics in this aspect.

In this paper, we call visualizing, analyzing and mining e-book activity logs “E-book-based Learning Analytics” (ELA). In such analytics, some researchers in the Kyushu University reported several analytics using a document viewer system called BookLooper (Ogata et al., 2015), (Yin et al., 2014), (Yamada et al., 2015). The objectives of their studies are as follows: (1) improving of learning materials, (2) analyzing learning patterns, (3) detecting students’ comprehensive level, (4) predicting final grades, and (5) recommending e-books in accordance with personalization. This paper focuses on (2) and (4). One of the issues of (2) or (4) is how to mine meaningful learning patterns for profiling high-achieving students.

To achieve the issue, this paper describes data mining method based on ELA. The rest of this paper is constructed as follows. Section “What is BookLooper” explains the functions of BookLooper such as next page, previous page, and bookmark. Section “Data Collection” describes logs for this analysis and then how to categorize them. Section “Method” describes analysis method for profiling high-achieving students. Section “Results” describes the results of analysis, and discussion regarding high-achieving students.

What is BookLooper?
Booklooper is a commercial product designed by Kyocera Maruzen Systems Integration Co., Ltd. The system provides a cloud service. Students can download learning materials by using the BookLooper viewer. The e-books are managed in the bookshelf. If students select a book in the bookstore, the book will be downloaded into the bookshelf. The students then choose the book in the bookshelf in order to read it in the viewer. By using viewer, students can use some functions such as next page, previous page, bookmark, underline, and annotation as shown in Figure 1. For example, if a student will click button such as zoom and marker, the action will be saved into the database. In the next section, this paper describes how we categorize e-book logs accumulated in the database.
Data collection

Categorization of academic achievement

Logs for this analysis were collected from 99 first-year students via BookLooper and Moodle. These students took an information science course in the second semester of the 2014/2015 school year at the Kyushu University. The number of logs are collected approximately 330,000. We use Moodle to manage students’ attendance, mid-semester test score, end-of-term test score, and report score. Also, BookLooper is used for collecting students’ operation logs and three types of learning time of each student: Preparation Time Before Class (BTBC), Learning Time During Class (LTDC), and Review Time After Class (RTAC) using BookLooper for profiling the relationships among high-achieving students, BTBC, LTDC and RTAC because students who devoted much time to prepare and review are not necessarily good score. In addition, it is important to categorize them efficiently in order to detect or mine meaningful learning patterns for profiling high-achieving students. Therefore, we divide numerical data such as the number of attendance, lateness and absence, report scores, mid-semester test scores, end-of-term test scores, three types of learning time and final score to several categories excluding numerical data. This paper establishes criteria for categorizing them as shown in Table 1. The high-achieving students of the top 20 percent mean A rank. For example, if a student devoted much time more than 2364 seconds in order to prepare the content by the next lesson using BookLooper, we categorize the student to “BTBC = A rank”.

Table 1: The criteria for categorizing the achieving rank of each student

<table>
<thead>
<tr>
<th>LV</th>
<th>Criteria</th>
<th>Attendance (Scoring 30)</th>
<th>Report (Scoring 40)</th>
<th>Mid-semester (Scoring 10)</th>
<th>End-of-term (Scoring 20)</th>
<th>BTBC (seconds)</th>
<th>LTDC (seconds)</th>
<th>RTAC (seconds)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>Top 20%</td>
<td>&gt;= 23</td>
<td>&gt;= 35</td>
<td>&gt;= 9</td>
<td>&gt;= 16</td>
<td>&gt;= 2364</td>
<td>&gt;= 32025</td>
<td>&gt;= 10718</td>
</tr>
<tr>
<td>C</td>
<td>40 – 60</td>
<td>18 – 21</td>
<td>20 – 30</td>
<td>8 – 8.5</td>
<td>12 – 14</td>
<td>76 – 676</td>
<td>19159 – 27053</td>
<td>3907 – 6735</td>
</tr>
<tr>
<td>E</td>
<td>80-100</td>
<td>14&gt;=</td>
<td>15&gt;=</td>
<td>7&gt;=</td>
<td>10&gt;=</td>
<td>0</td>
<td>12946=</td>
<td>785&gt;=</td>
</tr>
</tbody>
</table>

Questionnaires

The students were required to answer questionnaires before class in order to investigate their life styles, a method and time of transportation to university, the amount of learning for one day, and satisfaction of university life. Table 2 shows the questionnaires. Q1 and Q2 ask about their life style in the morning such as breakfast and time to get up because the class of the information science course starts in the morning. Q3 and Q4 ask about their commuting method and time in order to analyze relationships among high-achieving students, commuting method and time. Q5 asks about the amount of their study time for one day. Q6 asks about satisfaction of their university life. In the next section, this paper describes how to mine meaningful learning
patterns for profiling high-achieving students using these data as described Sections titled “Categorization of academic achievement” and “Questionnaires”.

Table 2: Questionnaires

<table>
<thead>
<tr>
<th>Question items</th>
<th>Answer items</th>
</tr>
</thead>
<tbody>
<tr>
<td>Q1 What time do you get up?</td>
<td>(1) before am 5:00 (2) am 5:00<del>6:00 (3) am 6:00</del>7:00 (4) am 7:00<del>8:00 (5) am 8:00</del>9:00 (6) after am 9:00</td>
</tr>
<tr>
<td>Q2 Do you eat breakfast every day?</td>
<td>(1) Yes (2) No</td>
</tr>
<tr>
<td>Q3 What do you use a method of transportation to university?</td>
<td>(1) on foot (2) bicycle (3) car (4) public transport</td>
</tr>
<tr>
<td>Q4 How many do you take to university?</td>
<td>(1) less than 30 minute (2) 30<del>60 minute (3) 60</del>90 minute (4) 90~120 minute (5) more than 120 minute</td>
</tr>
<tr>
<td>Q5 How much time do you study for one day</td>
<td>(1) more than 3 hours (2) 2<del>3 hours (3) 1</del>2 hours (4) less than 1 hour</td>
</tr>
<tr>
<td>Q6 Do you feel that university life is fun?</td>
<td>(1) Extremely well (2) Very well (3) Moderately well (4) Slightly well (5) Not at all well</td>
</tr>
</tbody>
</table>

Methods

Data mining based on e-book-based learning analytics

In order to mine meaningful learning patterns for profiling high-achieving students, this paper uses an association analysis with Apriori algorithm. Association analysis is one of the popular analysis methods in order to mine regularities between some parameters of educational big data. For example, Mouri et al. (Mouri et al., 2015) use association analysis for mining useful learning patterns from learning logs accumulated in ubiquitous learning system called SCROLL. The objective of SCROLL is to support international students to learn learning object in Japanese in an informal setting. In addition, they believe that visualizing and analyzing them collected by SCROLL lead to enhancing students’ learning activities in an informal setting. Unlike Informal Learning Analytics (ILA) or Ubiquitous Learning Analytics (ULA) of their focus, this paper focuses on analyzing logs collected in a formal and an informal setting. The analysis of this paper was conducted the following those criteria: Support ≥ 0.3, Confidence ≥ 0.6, Lift ≥ 1.0. The objective of the setting value is to detect many association rules as far as possible. The number of the detected association rules is 51,641. In order to find meaning learning patterns for profiling high-achieving students, this study mines association rules that the conclusion parts are score A rank as described in section titled “Categorization of academic achievement”.

Results

Profiling and discussion

In order to find the relationships between high-achieving students and the effectiveness of BookLooper, and high-achieving students and the questionnaires as shown in Table 2, this paper investigates the association rules that the conclusion parts are “report score is rank A”, “mid-semester test score is rank A”, “end-of-term test score is rank A” and “final score is rank A”. We found important some association rules shown in Table 3.

The rules from 1 to 5 show that the conclusion part is report score A rank. The “BTBC=A” of the rule 1 means that students devoted much time more than 2364 seconds in order to prepare by the next lesson. The relationships between “BTBC=A” and high-achieving students have a high relativity because the confidence value of the rule 1 is 1. The rule 2 and 5 show that the condition parts are “Q1= (3) && Q4= (1)” and “Q2= (1) && Q4= (1)”. This means the commuting time of high-achieving students to university is less than 30 minutes. In addition, they get up early in the morning and eat breakfast every day.

The rules from 6 to 10 show that the conclusion part is mid-semester test score A rank. The rule 6 and 8 show that the condition parts are “attendance = A & & report=A” and “attendance = A && Q1= (3)”. In order to achieve the mid-semester test score A, it indicates that it is important to get attendance score more than 23 points. The rule 9 and 10 shows that the relationships between “report=A && Q4= (1)” and mid-semester test score, and “report=A && Q2= (1)” and mid-semester test score.

The rules from 11 to 15 show that the conclusion part is end-of- term test score A rank. The “LTDC =A” of the rule 12 means that students devoted much time more than 32025 seconds using BookLooper during class. In addition, the “RTAC = A” of the rule 13 means that students devoted much time more than 10718
seconds using BookLooper in order to review the content after class. That means that it is important to achieve the conditions of "RTAC=A" and "LTDC=A" if students want to get the end-of-term test score A rank.

The rules from 16 to 20 show that the conclusion part is final score A rank. The rule 16 and 17 means that the condition part is “BTBC=A” and “RTAC=A”. That means that it is important to achieve the two conditions if students want to get final score A rank. Conversely, if students have “BTBC=E” or “LTDC=E”, Most of them got final score E rank as shown in Figure 2. Therefore, there is a possibility that the profiling high-achieving students lead to discoveries of students who fail to make the grade.

Table 3: The association rules among high-achieving students, BookLooper and questionnaires

<table>
<thead>
<tr>
<th>No</th>
<th>Condition part</th>
<th>Conclusion part</th>
<th>Support</th>
<th>Confidence</th>
<th>Lift</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>BTBC=A</td>
<td>report=A</td>
<td>0.306592</td>
<td>1</td>
<td>1.1124948</td>
</tr>
<tr>
<td>2</td>
<td>Q1=(3) &amp; &amp; Q4=(1)</td>
<td>report=A</td>
<td>0.401229</td>
<td>0.9571007</td>
<td>1.0647695</td>
</tr>
<tr>
<td>3</td>
<td>Q6=(1)</td>
<td>report=A</td>
<td>0.4007834</td>
<td>0.8488891</td>
<td>1.0443846</td>
</tr>
<tr>
<td>4</td>
<td>Q5=(3)</td>
<td>report=A</td>
<td>0.3476144</td>
<td>0.934392</td>
<td>1.0395062</td>
</tr>
<tr>
<td>5</td>
<td>Q2=(1) &amp; &amp; Q4=(1)</td>
<td>report=A</td>
<td>0.3178796</td>
<td>0.9464546</td>
<td>1.0529258</td>
</tr>
<tr>
<td>6</td>
<td>attendance=A &amp; &amp; report=A</td>
<td>mid-semester test score =A</td>
<td>0.301626</td>
<td>0.636362</td>
<td>1.0298533</td>
</tr>
<tr>
<td>7</td>
<td>Q4=(1)</td>
<td>mid-semester test score =A</td>
<td>0.3316247</td>
<td>0.6048627</td>
<td>1.0437379</td>
</tr>
<tr>
<td>8</td>
<td>attendance=A &amp; &amp; Q1=(3)</td>
<td>mid-semester test score =A</td>
<td>0.3099994</td>
<td>0.6178257</td>
<td>1.0794652</td>
</tr>
<tr>
<td>9</td>
<td>report=A &amp; &amp; Q4=(1)</td>
<td>mid-semester test score =A</td>
<td>0.3406835</td>
<td>0.7807266</td>
<td>1.1487107</td>
</tr>
<tr>
<td>10</td>
<td>report=A &amp; &amp; Q2=(1)</td>
<td>mid-semester test score =A</td>
<td>0.3068324</td>
<td>0.8832242</td>
<td>1.1863906</td>
</tr>
<tr>
<td>11</td>
<td>Q1=(3) &amp; &amp; Q2 =(1)</td>
<td>end-of-term test score=A</td>
<td>0.3007997</td>
<td>0.8368737</td>
<td>1.319224</td>
</tr>
<tr>
<td>12</td>
<td>LTDC=A</td>
<td>end-of-term test score=A</td>
<td>0.313928</td>
<td>0.6541544</td>
<td>1.1640735</td>
</tr>
<tr>
<td>13</td>
<td>RTAC=A</td>
<td>end-of-term test score=A</td>
<td>0.3313667</td>
<td>0.8179246</td>
<td>1.255504</td>
</tr>
<tr>
<td>14</td>
<td>report=A &amp; &amp;LTDC=A</td>
<td>end-of-term test score=A</td>
<td>0.3049478</td>
<td>0.6906759</td>
<td>1.2290638</td>
</tr>
<tr>
<td>15</td>
<td>attendance=A report=A LTDC=A</td>
<td>end-of-term test score=A</td>
<td>0.3049478</td>
<td>0.6906759</td>
<td>1.2290638</td>
</tr>
<tr>
<td>16</td>
<td>BTBC=A</td>
<td>final score=A</td>
<td>0.4007834</td>
<td>0.8488891</td>
<td>1.0443846</td>
</tr>
<tr>
<td>17</td>
<td>RTAC=A &amp; &amp; Q1=(3)</td>
<td>final score=A</td>
<td>0.3476144</td>
<td>0.934392</td>
<td>1.0395062</td>
</tr>
<tr>
<td>18</td>
<td>Q1=(3) &amp; &amp; Q2=(1)</td>
<td>final score=A</td>
<td>0.306592</td>
<td>1</td>
<td>1.1124948</td>
</tr>
<tr>
<td>19</td>
<td>mid-semester=A &amp; &amp; end-of-term=A</td>
<td>final score=A</td>
<td>0.401229</td>
<td>0.9571007</td>
<td>1.0647695</td>
</tr>
<tr>
<td>20</td>
<td>Q4=(1)</td>
<td>final score=A</td>
<td>0.4007834</td>
<td>0.8488891</td>
<td>1.0443846</td>
</tr>
</tbody>
</table>

Figure 2. The number of student of “final score = E rank”: The blue bar shows BTBC = E rank”, the red bar shows “LTDC = E rank”
Conclusion
This paper describes how to mine or detect meaningful learning patterns for profiling high-achieving students using e-book-based activity logs. In order to mine the learning patterns, this paper uses association analysis with Appriori algorithm. The analysis was conducted to find the relationships between high-achieving students and the effectiveness of a document viewer system called BookLooper as shown in Table 2, and high-achieving students and the questionnaires as shown in Table 3. In addition, this paper investigated the association rules that the conclusion parts are “report score is rank A”, “mid-semester test score is rank A”, “end-of-term test score is rank A” and “final score is rank A”. In the future, we will consider supporting students who fail to make the grade using the detected association rules. Also, we will consider visualizing various methods such as social network analysis (Ogata et al., 2015) and visualization of graph theory (Mouri et al., 2014), and then develop system for recommending to the personal learner in accordance with the detected results. In addition, we will integrate e-book and SCROLL with task-based learning called Learning Log Navigator (Mouri et al., 2013) in order to enhance learning experience.

References

Acknowledgments
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One Competency Data Model to Bind Them All

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Abstract: Although students regularly demonstrate career-relevant competencies in post-secondary programs, it is difficult to document and communicate these accomplishments beyond the institution. Portfolios and microcredentials are intended to help solve these problems, but neither have been widely adopted or regularly expected amongst hiring managers. This paper speculates that a significant barrier to adoption has been the absence of a shared competency data model for educators and human resource professionals. A competency data model used to solve educational technology interoperability problems is presented. Discussion highlights synergistic projects that, if connected via a shared competency data model, could help adults advocate for their career goals using evidence from multiple contexts.

Keywords: competency-based education, data model, transcript, learning analytics

“The diploma, by remaining tied to no standard other than credit accrual and seat time, provides no useful information about what students have studied or what they can actually do with what was studied.” (Wiggins, 1989).

Introduction

The field of learning analytics suffers from a dearth of student learning data. Current research relies on indirect proxies, such as a student’s grade point average, particular course grades, or test performances, instead of authentic demonstrations of important competencies. For example, 70 percent of the fifty-one empirical studies included in a recent literature review used GPA as a dependent variable, with the remainder consisting of self-reports, credits, and exams (Gray, McGuinness, Owende & Carthy, 2014). Such indirect measures may yield valuable findings relative to institutional productivity, but they are insufficient to provide information about the processes and correlates of student learning for several reasons. Grades summarize performance relative to multiple course objectives, intermixing student learning with attendance, timeliness, engagement, punctuality, and other factors. Grades are also distributed according to a fixed, predetermined academic calendar that is not sensitive to each student’s specific learning curve. Moreover, historical research has demonstrated grade inflation patterns over the past several decades that don’t track with increases in students’ study habits or measured learning outcomes (Arum & Roksa, 2011). Presumably, learning analytics researchers primarily rely on weak measures of student learning because better measures are not readily available.

The resurgent interest in competency-based education (CBE) has the potential to rectify the shortcomings of grades for learning analytics research by providing programmatic, direct measures of student learning over time (Johnstone & Soares, 2014; Ford, 2014). In CBE programs, students advance based on demonstrated learning rather than on seat time or attendance. Needless to say, assessments are important in CBE programs. In mature CBE programs, faculty members, subject matter experts, and specialists collaborate to design assessments that simulate anticipated performance conditions and require students to draw upon multiple competencies simultaneously (McCarty & Gaertner, 2015). In the United States, the federal Department of Education has publicly encouraged institutions to develop CBE programming; current estimates project that about six hundred institutions are either currently designing or already implementing such programming (Fain, 2015).

CBE Interoperability

Several educational technology barriers have limited the growth of CBE. Established CBE programs have long managed these problems locally by developing custom applications and services, but new entrants can find these barriers formidable. The Technical Interoperability Pilot (TIP) project surveyed mature CBE programs and revealed several common interoperability barriers to CBE programming (Leuba, 2015). In response, IMS Global and the Competency-Based Education Network issued five formal requests for proposals and ten educational technology companies were selected to develop prototype solutions (see Table 1 for a list of contributing
vendors and use cases). Over a ninety-day period in 2015, these vendors collaborated with one another to prototype interoperability solutions using a shared competency data model (1). These solutions are envisioned to help institutions focus on serving the needs of their students and not integrations amongst multiple educational technologies (2).

Table 1: Vendor participants for CBE use cases and shared data model

<table>
<thead>
<tr>
<th>Vendor</th>
<th>Manage Competencies</th>
<th>Evaluation Results</th>
<th>Program Information</th>
<th>Substantive Interaction</th>
<th>Record of Performance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Blackboard</td>
<td></td>
<td>X</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>D2L</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ellucian</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Workday</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>eLumen</td>
<td></td>
<td></td>
<td></td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Flatworld</td>
<td></td>
<td></td>
<td></td>
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<td></td>
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<tr>
<td>Oracle</td>
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<td></td>
<td>X</td>
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<tr>
<td>Regent</td>
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<td></td>
<td></td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Accreditrust</td>
<td></td>
<td></td>
<td></td>
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<td>X</td>
</tr>
<tr>
<td>Learning Objects</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>X</td>
</tr>
</tbody>
</table>

Properties of a Shared Competency Data Model

A key deliverable of the 2015 CBE interoperability prototypes was a shared competency data model (See Figure 1). This model was used to define a JSON-LD web service supporting the transmission of a student’s *extended transcript* (3). Relative to the argument of this paper, there are four key properties of the competency data model that support its flexibility for CBE interoperability within an institution and potential data integration schemes that go beyond the institution.

**Competency hierarchy**

Most CBE curriculum models contain a hierarchical structure of competency statements. Some products support hierarchical relationships, but they do so in idiosyncratic ways that are specific to each product. The data model supports competency hierarchies using simple parent-child relationships via “isChildof” and “hasChild” fields. Another key feature of the data model is the inclusion of a “reference hierarchy” entity that is envisioned to describe a particular competency in relation to common frameworks. By supporting competency hierarchies in the data model, vendors help institutions sustain coherent programming across many technology tools for student-level reporting.

**Competency type**

Many analysts have noted that CBE programs use inconsistent terminology across institutions. Educational technology products have addressed this inconsistency by using very generic language in their products, which rarely supports any program well. The data model supports institution-specific terminology via a “type” field in the competency table. By supporting this feature of the data model, educational technology vendors empower institutions to sustain and control their curricular models.

**Competency code**

Many technology products have proprietary mechanisms for storing competency statements. Institutions utilizing multiple technology products for CBE programming often need to reference the same competency statement in different products, such as when assessing students using one tool and storing competency results in another tool. The prototype team envisioned solving this challenge by using a “competency code” with an associated effective date for versioning. A competency code is a logical reference to the full competency statement. It is analogous to a course code, such as PSY101 as a reference to an institution’s introductory psychology course. Competency referencing via a competency code and effective dates will allow an institution...
to reference the same competency statement across multiple products without relying on increasingly elaborate synchronization services for unique ids and versions.

**Competency scores**

CBE programs need to aggregate student-level data for particular competencies across multiple assessments and varied time periods. The data model supports such aggregation via a competency score table indexed by a competency_offering_map table. This approach permits institutions to report student-level competency scores based on the institution’s assessment strategy for each competency. For example, one competency may be assessed in multiple courses, whereas another competency may be assessed in only one specific course. The competency score table also supports competency-specific calculation methods to provide programming flexibility.

![Shared Competency Data Model](image-url)

**Figure 1. Shared Competency Data Model**
Speculations on CBE Data Integration

A shared competency data model not only helps institutions deploy their programming; it also advances a system for connecting higher education institutions with employers via digital credentials. For over a century, the student transcript has maintained its connection to the Carnegie unit standard for credits (Silva, White & Toch, 2015), but this focus is now being supplemented at many institutions with an extended transcript (eT) that includes detailed competency demonstration information (Black, Leuba, Owczarek, Parks & Shendy, 2016). The eT is intended to help students conceptualize their educational experience in a richer framework than what may be possible with courses, grades, and credits. Such metacognitive reflection may promote the intentionality and motivation some students need to complete their degree programs. For example, there is some evidence that utilization of a competency map dashboard is associated with higher rates of persistence, even after controlling for several powerful covariates (Grann & Bushway, 2014). The eT is also intended to help students advocate for their career goals with hiring managers.

Because these extended transcripts are secure digital documents (specifically packaged via JSON-LD), they could also serve as a basis for a broader data integration scheme. Students regularly participate in a variety of civic, volunteer, and employment contexts in which career-relevant competencies are acquired and demonstrated. While not common practice, some employers are also articulating key competencies for positions in their organizations (Franklin & Lytle, 2015). Currently, these accomplishments are documented individually on paper via a résumé or a curriculum vitae. While some companies have created text-mining algorithms to decode and digitize these text documents for analytic and recruitment purposes (such as Burning Glass and CareerBuilder), a far more efficient solution would be to standardize competency demonstration evidence using a shared competency data model.

Three synergistic projects make the prospect of a shared competency data model more probable than it might seem. The Credential Transparency Initiative (CTI) is focused on building a modern credential registry using a consistent vocabulary (4). CTI intends to include competencies in its credential domain model and to provide this information using linked data. Similar to IMS Global for educational technology, HR OpenStandards tries to solve interoperability problems with human resource technical systems (5). Based on a cursory analysis of HR OpenStandards, a competency data model is used to support hiring and performance management functions; this seems similar in structure to the shared competency data model. Because both of these models rely on linked data relationships packaged via JSON-LD, an equivalency between the competency data models can be established (Allemang & Hendler, 2011) to link the evidence on an extended transcript with CTI’s credential registry and the competency model used in HR OpenStandards. Moreover, these relationships linking higher education and employers can operate in both directions and provide a new mechanism to formally recognize documented competency demonstrations occurring within employment contexts, such as performance reviews. The Lumina Foundation has also supported the development of a Beta Credentials Framework that provides a metadata schema for describing competencies in a consistent manner (6). Although only now being field tested, this framework is conceptually consistent with the competency data model’s concept of “reference hierarchy” and, if broadly adopted, could help establish much-needed competency equivalencies and exchanges. If these promising initiatives could be integrated via a common data model, higher education has the potential to establish a lifelong learning digital credentialing system across multiple contexts that empowers students to articulate their learning outcomes and advocate for their career goals.

Endnotes
(1) The IMS Global website provides more context and information about this project at the following link: https://www.imsglobal.org/initiative/enabling-better-digital-credentialing.
(2) The following video provides an overview of the five CBE interoperability barriers and developed prototypes: https://www.youtube.com/watch?v=Eo5cnT6QVP4
(3) A working prototype of the extended transcript is available at the following link: https://demo-cbl.difference-engine.com/extended-transcript/
(4) More information about the Credential Transparency Initiative is available at the following link: http://www.credentialtransparencyinitiative.org/.
(5) More information about HR OpenStandards is available at the following link: http://www.hropenstandards.org/.
(6) More information about the Beta Credentials Framework is available at the following link: https://www.luminafoundation.org/resources/connecting-credentials.
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Toward the integration of monitoring in the orchestration of across-spaces learning situations

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Abstract: Technologies such as augmented Reality (AR), 3D Virtual Worlds (3DVWs) and mobile phones are extending education to other spaces beyond the classroom or the Virtual Learning Environments (VLEs). However, the richness of across-spaces learning situations that could be conducted in all these spaces is hampered by the difficulties (encompassed under the “orchestration” metaphor) that teachers face to carry them out. Monitoring can help in such orchestration, and it has been highly explored in face-to-face and blended learning. Nevertheless, in ubiquitous environments it is usually limited to activities taking place in a specific type of space (e.g., outdoors). In this paper we propose an orchestration system which supports the monitoring of learning situations that may involve web, AR-enabled physical and 3DVW spaces. The proposal was evaluated in three authentic studies, in which a prototype of the system provided monitoring through a web dashboard, an AR app, and a Virtual Globe.

Keywords: Learning analytics, monitoring, across-spaces, VLE, augmented reality, virtual worlds

Introduction

A multiplicity of technologically enabled learning spaces is emerging due to the technological advances of the last decades. Physical spaces such as classrooms, parks, museums or houses, are enriched with a variety of electronic devices: interactive whiteboards, computers, mobile phones, tablets, tabletops, etc. These devices are actually doors to other virtual learning spaces, like the Web or even 3D virtual worlds (3DVWs), in which learning is mediated by software tools, such as web Virtual Learning Environments (VLEs, e.g., Moodle¹), 3DVWs platforms (e.g., Second Life²) or Virtual Globes (VGs, e.g., Google Earth³). There has been substantial research focused on the continuity of the learning experience across-spaces where the students may benefit from the affordances of the different spaces while learning anytime anywhere (Milrad et al., 2013). Technologies such as mobile devices, sensors, and Augmented Reality (AR, i.e., the combination of virtual and physical objects in a physical environment) help connect different spaces, enabling across-spaces learning situations (Wu, Lee, Chang, & Liang, 2013). For instance, a virtual object generated by a group of students in a classroom can be afterwards used in-context in a park with AR. Actually, when learning across-spaces, there is a special emphasis on the physical context where the learning activity takes place, which is a core factor in the typical educational approaches involving different spaces (Milrad et al., 2013).

Despite the benefits that across-spaces learning situations may provide, teachers still face several difficulties to create and conduct this kind of situations (Delgado Kloos, Hernández-Leo, & Asensio-Pérez, 2012). These difficulties to create and enact learning situations in technologically complex educational settings (not only across-spaces) have been encompassed by the research community under the “orchestration” metaphor (Prieto, Dlab, Gutiérrez, Abdulwahed, & Balid, 2011). Across-spaces learning situations, where the activities frequently involve a number of separate groups interacting simultaneously from distant locations using different technologies, pose special requirements to orchestration. One of these requirements is that teachers lose awareness of what students perform, and need special help to keep track of the development of the activities and the progress (or lack thereof) of the different groups. One of the key functions that can help teachers in the orchestration of these settings is monitoring. Monitoring is the collection of data related to specific indicators, which provides different stakeholders of a development intervention with indicators regarding the progress and results of such intervention (Marriott & Goyder, 2009). Monitoring can be understood as a shared task between

the system and the user (i.e., the teacher or the student), where the response given by the system can range from showing the state of the interaction without much processing to the user, leaving the responsibility of interpreting the data to the user (mirroring); to more ‘intelligent’ approaches that analyze the state of the interaction and present direct advice to the user (guiding) (Soller, Martínez, Jermann & Muehlenbrock, 2005).

In across-spaces learning situations, where, as mentioned, typically the physical context is relevant, context-aware data usually needs to be collected using a variety of devices, such as sensors, and be integrated with the already heterogeneous data of traditional distributed educational systems (e.g., VLEs, Web 2.0 tools, social applications, etc.). However, despite the need for monitoring solutions in across-spaces situations to help orchestration (Long & Siemens, 2011), research in this field is still in its infancy. Most of the orchestration approaches considering physical spaces beyond the classroom propose solutions for monitoring the activities only in those physical spaces, typically using mobile devices, without integrating such data with data coming from other learning activities, spaces or devices (e.g., accesses to a web 2.0 tool such as Google Drive). These monitoring proposals are usually classified into ubiquitous or pervasive learning analytics (ULA or PLA) and mobile learning analytics (MLA) (Aljohani & Davis, 2012; Shoukry, Göbel, & Steinmetz, 2014) depending on whether the monitoring collects context-aware data (e.g., Facer et al., 2004; Santos, Hernández-Leo, & Blat, 2014) or not (Seol, Sharp, & Kim, 2011). Alternative approaches are weSPOT (Miteva, Nikolova, & Stefanova, 2015), which integrates the data of activities carried out in different spaces but lacks of context-aware information, or the system proposed by Tabuenca, Kalz, & Specht (2014), that provides contextual information but does not integrate data coming from other activities or spaces.

Therefore, to the best of our knowledge, there is a scarcity of orchestration proposals enabling the monitoring of across-spaces learning situations in which activities can take place in different physical and virtual spaces. In this paper we describe our research in this issue. Section 2 describes Glueps-maass, our proposal for the orchestration of across-spaces learning situations including activities in physical, web and 3DVW spaces and making use of a variety of existing technologies. Section 3 summarizes the main happenings and results of the evaluation carried out, which comprised three studies in authentic settings. Finally, in Section 4, we present the main conclusions obtained in the research.

**Glueps-maass**

During the latest years, we have been exploring in parallel the orchestration of across-spaces learning situations (Muñoz-Cristóbal, 2015), and the design-aware monitoring of blended learning situations (Rodríguez-Triana, 2014). For the former issue, we proposed GLUEPS-AR, a system to support teachers in multiple aspects of orchestration of learning situations that may involve activities in web (using VLEs), physical (using AR apps) and 3DVW (using VGs) spaces. GLUEPS-AR is able to offer user-awareness in the enactment platforms (by showing avatars in the enactment platforms), and it provides a user interface in which teachers can access the design, and the different artifacts created by the students. However, GLUEPS-AR does not provide with a dashboard with aggregated information. Consequently, Glueps-AR showed to be complex for teachers since they could not access a single source of information to understand what happened during the enactment of the learning situation. Additionally, in the other research line regarding the monitoring of blended learning, we proposed two systems, GLUE!-CAS and GLIMPSE, aimed at supporting monitoring by gathering, integrating and analyzing data based on the information provided by the learning design. GLUE!-CAS and GLIMPSE are able to collect data from heterogeneous sources (web-based blended learning environments and participants feedback), and to provide teachers with monitoring reports structured according to the learning designs initially defined. However, this approach is focused on blended learning, without taking into consideration learning situations happening in other non-web spaces, like the physical or 3DVWs.

Interestingly, the two approaches complement very well, since each one could cover the main orchestration limitations of the other. Furthermore, both approaches share a same technological architectural philosophy, since they both are based on the well-known *adapter pattern* of software engineering in order to facilitate the integration of multiple technologies. Therefore, we can easily abstract both approaches and combine them, following the conceptual model proposed by Martínez-Maldonado et al. (2013), in a new system integrating their orchestration features. The resulting system is Glueps-maass (Group Learning Unified Environment with Pedagogical Scripting, Monitoring, Analysis and Across-Spaces Support), whose architecture is described in Figure 1 (left). Glueps-maass provides support to the multiple aspects of orchestration, enabling teachers to deploy their learning designs, which may have been created with multiple authoring tools, into enactment settings that can be composed by multiple web VLEs, AR apps and VGs. Teachers can also manage and adapt the across-spaces learning situations at runtime through a user interface. Different virtual artifacts (e.g., Web 2.0 tools such as Google Docs) can be accessed from any of the spaces, due to the possibility of integrating in Glueps-maass multiple artifact-providers or Distributed-Learning-Environment adapters (e.g.,
GLUE! or IMS-LTI\(^4\), see Alario-Hoyos & Wilson, 2010). In addition, the system is able to collect and integrate data from the multiple sources available in the learning scenario. Such data can be subsequently visualized at runtime and/or after the enactment both in a dashboard or using the enactment technologies (e.g., representing the location of the students in VLEs, AR apps and/or VGs by means of an avatar). Following the design-aware monitoring process inherited from GLIMPSE, the monitoring reports inform about the progress of the learning activities with respect to the teachers’ pedagogical intentions represented by the learning design. These reports can be personalized according to the teachers’ interests and taking into account contextual variables relevant in these contexts (e.g., a teacher can decide that s/he wants to monitor the number of times a group visits a position in a specific phase of the designed activity, while another can decide s/he wants to monitor the number of files uploaded by the participants in a particular location at another phase, etc.).

Aiming to evaluate the monitoring support of Glueps-maass, we developed a prototype (see Figure 1, right) integrating GLUEPS-AR, GLIMPSE and GLUE!-CAS. The prototype has been evaluated in different authentic across-spaces learning situations, which are described in the next section.

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**Figure 1.** Glueps-maass architecture (left) and implemented prototype (right)

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**Intervention**

We followed the Systems Development Research Methodology (Nunamaker, Chen, & Purdin, 1990) with an underlying interpretive perspective (Orlikowski & Baroudi, 1991) for the overall research process, as well as the Evaluand-oriented Responsive Evaluation Model (EREM; Jorrín-Abellán & Stake, 2009) as a framework for the evaluation. The research question we posed was *how can technology help integrate monitoring in the orchestration of across-spaces learning situations?* This research question was refined by means of a data-reduction process (Miles & Huberman, 1994) that led us to focus on a reduced set of topics, two of which are relevant for this paper: i) the support of the system to monitor across-spaces learning situations and ii) the affordability of the proposed solutions for the participant teachers.

To address the research question we proposed the architecture and developed a prototype of the Glueps-maass system, which was used in three studies involving authentic educational settings (see Muñoz-Cristóbal, 2015, for more information about the studies). We used multiple data gathering techniques, such as interviews, web-based questionnaires, participant observations and collection of teachers and students’ generated artifacts (e.g., teachers’ emails, learning materials and outcomes). The next paragraphs describe the three studies, which took place in 2013 in Spain.

**Study1: Orientate!**

*Orientate!* is an across-spaces learning situation carried out by a pre-service teacher in his practicum. It was conducted with a class with 18 students of around 12 years old, in a course on Physical Education belonging to the official curriculum of a primary school. The situation was composed of 5 sessions taking place in different physical and web spaces: the classroom, the school’s playground, a nearby park, and a wiki-based VLE. Many technologies were used, such as an interactive whiteboard, netbooks, tablets, Web 2.0 tools and the Junaio\(^5\) mobile AR app. The objective of the learning situation was to help develop orienteering skills in the children.

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\(^5\) [https://my.metaio.com/dev/junaio](https://my.metaio.com/dev/junaio), Last access January, 2016

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During the activities, the pre-service teacher and the students created different virtual artifacts, which were afterwards accessed from a different space from where they were created. For instance, they created geolocated quizzes using Google Docs⁶ in the VLE while staying in the classroom, which later on were accessed at specific locations in the park using the Junaio AR app.

In this study, Glueps-maass supported the pre-service teacher in different orchestration aspects (such as in deploying the learning situation in the enactment setting, in managing the learning activities, or in adapting them when facing emerging events). Regarding monitoring, by means of the adapters, Glueps-maass collected data from the different technologies used in the different spaces (Junaio, Web 2.0 tools, wiki-based VLE), which were processed by the Glueps-maass manager and stored in the internal repository. Both the Glueps-maass user interface and the wiki-based VLE served as a control panel for the teacher, since he could view and access what the students did. In addition, after the end of the activities, the pre-service teacher reviewed the actions conducted by the students using a report produced by the Glimpse dashboard (see Figure 2, left). The report provided information about how the learning design unfolded, such as the number of accesses of the different groups of students to the different learning artifacts in each activity. The report did not provide context-aware information, since the prototype did not triangulate the information coming from the different sources. Thus, the pre-service teacher needed to access the Glueps-maass user interface, or the wiki, and consult the artifacts created by the students if he wanted, for instance, to be aware of the location where an artifact had been generated. Other context-aware interaction data was stored in the internal repository, but not provided to the pre-service teacher. The pre-service teacher valued as useful the wiki-based VLE to be aware and control the students’ actions in run-time during activities in the classroom, and the design-structured dashboard to understand what had happened and help him assess the work of students after the end of the activities. However, the teacher missed to be able to access the dashboard information at run-time during the enactment so that he could be aware of what students were actually doing. Other limitations highlighted by the pre-service teacher were the absence of location information in the dashboard, and the lack of runtime awareness in physical spaces outside the classroom (e.g., the park), where the students spread out over a huge area. He also indicated that a map, where the learning artifacts and the students’ actions could be tracked, would have been very useful. However, when asked about his opinion regarding the implementation of a dashboard in a tablet for accessing at runtime to the information he demanded, he considered that it would be complicated to be able to use it in activities such as the ones conducted outdoor.

Study2: Game of Blazons

*Game of blazons* is an across-spaces learning situation involving physical and web spaces, which was carried out by two teachers and 47 undergraduate students of a course on Physical Education in the Natural Environment, for pre-service teachers. The learning situation took place in a medieval village, together with other related learning situations conducted during a weekend in the village and its surroundings. The situation was aimed at helping students acquire different skills and knowledge of the subject (orienteering, hiking, history, culture and environment, etc.), as well as to be able to prepare and carry out physical education activities with children in a natural environment. The students, in groups, had to find (using orienteering skills) several stone blazons (coat of arms) chiseled in houses of the village. Close to each blazon, they had to use an AR app (Junaio or a QR code reader) in a mobile device to access Web 2.0 tools containing learning resources and instructions of different activities to be performed (quizzes, challenges, geocaching activities, etc.).

Before and after the session in the village, other blended activities were conducted in the classroom and online, with the help of the Moodle VLE. As in Study 1, Glueps-maass supported teachers in different aspects of orchestration, and regarding monitoring, context-aware data was collected by the different adapters, processed by the manager, and stored in the internal repository. In addition to user-interaction data, in this case we also collected periodically information about the user, containing its location in physical spaces. Also, we extended the prototype, and user information was sent from the manager to the AR adapters, in order to use the mobile AR apps to trace the participants, providing runtime user awareness using AR. During Game of Blazons, the students used Junaio to access AR learning resources, while the teachers could see the location of the different groups of students by means of avatars in Junaio (see Figure 2, centre).

Due to the characteristics of the learning situation, in which the teachers were overwhelmed, and also since the AR monitoring feature had been developed shortly before, the teachers did not monitored the position of the students continuously. Nevertheless, the main teacher used such feature in different occasions during the learning situation. In the final interview, he identified the AR user-awareness feature as one of the most interesting findings of the learning situation. He considered that it could be very relevant, for security reasons, in

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⁶ [https://www.google.com/docs/about/](https://www.google.com/docs/about/). Last access January, 2016
many learning activities performed with children. He also described other possible uses in different learning situations, such as for promoting collaboration in physical spaces (an expert student could help a learning partner). The main limitation emphasized by both teachers was the lack of a tracking feature in which they could observe (both in runtime and after the enactment) in a map the whole paths followed by the students (not just their runtime positions), with different information, such as learning artifacts involved, times devoted, being able to comment in runtime, etc. Finally, the possibility to access to the information anytime anywhere was identified by the students as one positive asset of the system, which helped them acquire and reinforce the learning contents in a motivating way.

**Study 3: 3D mirrored campus**

This study relied on an across-spaces learning activity involving web, physical and 3DVW spaces, in the frame of a review session of the different topics addressed in the same course on Physical Education in the Natural Environment for pre-service teachers. The same two teachers of the Study 2 participated, together with 48 students of the same class. The students performed the activity taking turns, in groups of 6 students (while a group was conducting the activity, the rest of the students were carrying out other different activities). The activity was complemented with pre- and post-tasks using Moodle, created by students and teachers. The objective of the activity was to assess and reinforce the spatial and orienteering abilities acquired during the course, showing them also some more complex technological setups. The 6 students had to split into two groups. One of the groups had to walk outdoors around the campus following whatever route they wanted, carrying a tablet with the Junaio AR app active. The other group, in a classroom, could follow the path of their learning partners, represented as an avatar in the 3D view of the Google Earth VG (see Figure 2, right). The students in the classroom had to draw in an orienteering paper map the path that the other group was following. When the group with the tablet returned to the classroom, they also had to draw their followed route in a paper map, and compare it with the map drawn by their colleagues. Afterwards, they changed roles and repeated the activity.

The main differences of this case with the other two described above are the inclusion of a new kind of space (a 3DVW), and the fact that the awareness of the users’ actions was provided to the students, in order to promote self-regulated and collaborative learning. As in the previous study, user’s context and interaction data was sent from the different spaces by the adapters to the manager, processed by the manager and stored in the internal repository. Also, user information was sent back from the manager to the adapters, in order to represent the location of the users by means of avatars. This way, the outdoor location in the physical space of a group of students using Junao was represented indoors in runtime by means of an avatar in the Google Earth 3D view of the campus. The main problem faced in this study was technological. It was the first usage of the VG user-awareness feature in a real setting, and the prototype did not support more than one user represented simultaneously in the VG (initially the teachers had conceived 3 members of the 6-students group carrying individual tablets). Later on, we solved these problems and we tested the prototype simulating more than 100 concurrent users. The teachers valued positively the use of Google Earth in the activity, asserting that it supported technologically a typical activity to develop orienteering skills that they had performed usually without technology (e.g., using post-its). Also, they thought that the activity had an important pedagogical sense and the aims were achieved. Furthermore, they perceived that it would be very useful for them to be aware of the students’ actions during the enactment of activities in physical spaces, although they considered the
available time as the main problem to be able to use it. Finally, they confirmed the necessity of tracking functionalities (during and after the enactment) to register in a map the routes, actions, and times performed by the students. It is also worth mentioning that among other pedagogical benefits, students stated that this situation had helped them get in touch with new technological resources to develop spatial perception, and to collaborate with partners tracing paths.

**Discussion, conclusions and future work**

We have proposed a new system, Glueps-maass integrating two existing orchestration approaches that emphasized different orchestration aspects: GLUEPS-AR and GLIMPSE/GLUE!-CAS. Glueps-maass aims at supporting teachers in the multiple aspects of orchestration of across-spaces learning situations, including the monitoring of the students’ actions. The three authentic settings where the system was evaluated - in terms of its monitoring aid for teachers - enabled us to assess some interesting and innovative characteristics of the proposal. In addition to providing monitoring support in across-spaces learning situations involving web, physical and 3DVWs spaces, Glueps-maass also provides across-spaces monitoring support, enabling monitoring in web, physical and 3DVW spaces, using, respectively, a web dashboard, an AR app and a VG. This not only increases the monitoring possibilities of the system, but it can also enrich its educational usage, enabling teachers to adapt the monitoring approach to their pedagogical ideas, or even to use monitoring as a didactic resource in their learning situations, as in Study 3. The use by the students of the Glueps-maass monitoring features is another interesting finding of the evaluation, since it assessed how Glueps-maass provides monitoring support to both teachers (in Studies 1 and 2) and learners (in Study 3). It is also relevant to underline the three Glueps-maass different monitoring options: The user interface, where a teacher can access (in runtime and after the enactment) to all the artifacts generated by the students; the dashboard, where relevant information is aggregated and organized according to the learning design; and the very same enactment technologies supporting the learning situation, which provide runtime user-awareness by means of avatars. The different Glueps-maass monitoring options showed they offer enough flexibility to be able to adapt to the needs of very different learning situations.

Besides the positive findings, the reported studies have been useful to identify challenges that need further exploration. These challenges address both run-time and post-hoc support. Regarding synchronous support, an important line of research is related to the design of tools that provide teachers with monitoring capabilities they are able to handle at runtime, since they are usually overwhelmed during the enactment, when the available time is limited and the monitoring tools could distract instead of help them. Another demand identified in the cases was the need of a tracking facility able to integrate the positioning information with other meaningful products of the learning situation that could help teachers and students to review and reflect on it.

The studies had some limitations that define our immediate future work. We plan to further explore the combination of the different monitoring features of the system, since each monitoring option was used in a different learning situation. In addition, some of the interaction-data gathered from the enactment technologies is not currently included in the visualizations. We need additional research in order to improve the monitoring features with this information, such as creating the tracking maps demanded by the involved teachers. In fact, the current version of Glueps-maass takes a humble approach to analysis, leaving to the teacher the responsibility for the interpretation of the data. We plan to enrich the existing system with more advanced analytical features and test whether more intelligent ways of support are effective to help teachers orchestrate across-spaces learning situations. Finally, further research would be necessary to explore the scalability of the approach so that it could eventually be used in massive educational environments.

**References**


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Automatic Generation of Personalized Review Materials Based on Across-Learning-System Analysis

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Abstract: In this paper, we propose a novel method to make a summary set of lecture slides for supporting students’ review study. Quizzes are often conducted in a lecture to check students’ understanding level. The aim of our study is to support a student who wrongly answers the quiz. The quiz statement is analyzed to extract nouns in the statement. Then, text mining is performed to find the pages related to the quiz statement in the relevant lecture materials. The proposed SummaryRank algorithm evaluates the topic similarity among pages in material with emphasizing the related page to the quiz statement. In addition, our proposed method considers the preview status of each student, resulting in the generation of adaptive review materials tailored for each student. Through experiments, we confirmed that the proposed method could find appropriate pages with respect to the quiz statements.

Keywords: Automatic generation, Personalized review material, e-Book, e-Learning system

Introduction

In a learning cycle, preview and review processes are very important for students. A preview process, i.e., studying in advance for a class, enables students to understand the class narrative, to become familiar with important keywords, and to discover new terms and concepts. Some studies such as Beichner (1995) report that good preparation prior to lectures leads to improved student performance. A review process, i.e., studying after a class, is also important not only to look back on the things that a student has learned in the lecture, but also to enrich one’s understanding of the lecture contents. Therefore, students are often asked to undertake preview and review study.

In terms of efficient study support, systems enabling the automatic creation of summaries of online audio/video presentations(He et al., 1999), spoken lectures(Chen et al., 2011), and sets of lecture slides(Shimada et al., 2015) have been proposed. These systems provide a brief summary of lecture contents so that students can perform efficient previewing and reviewing. Automatic quiz generation systems have also been proposed by many researchers to support students’ self-learning and enhance their understanding of lecture contents (Aldabe et al., 2006; Liu et al., 2010; Sathiyanarurthy and Geetha, 2012; Liu et al., 2012). Text analysis or natural language processing (NLP) is applied to input text to extract important keywords. Then, a quiz is automatically generated to check the understanding level of students. This system is useful not only for students but also for teachers, since they need not expend any effort in compiling the quiz. To clarify the standpoint of our research, we categorize the automatic quiz generator as a forward type of support system, where text in lecture materials is used as the input to a system, which then produces output in the form of quizzes.

Conversely, in this paper, we proposed a backward type of support system, whereby quiz results are used as input to a system, and then the corresponding pages of lecture materials are automatically salvaged. Such inverse correspondence is very important for the efficient provision of review material for students. The most noteworthy characteristic of the proposed system is that it adapts review material to the requirements of each student based on not only their academic performance but also their preview behavior. To achieve such tailored support, we utilize the 1 e-Book system for the collection of preview behavior performed in the physical space and e-Learning system for the collection of academic performance in the cyber space.

Automatic Generation of Review Material

Figure 1: Overview of proposed review summarization system

An overview of the automatic generation of personalized review materials is shown in Figure 1. First, quiz results are analyzed to determine whether or not a student answered correctly. If he/she answered incorrectly, the corresponding quiz statement is used as an input to the proposed system. A text analysis is then performed to find related pages.
Second, the lecture material is analyzed for topic similarity. This process is based on the concept that pages containing similar content should be included in the review material. Third, preview achievement is analyzed using page view logs in the e-Book system.

Finally, the related page mining, topic similarity, and preview achievements are holistically evaluated to generate a summary of the material. The details of each process are provided in the following sections.

**Related Page Mining**

Our strategy assumes that a related page contains the same keyword as the quiz statement. Each quiz statement $QS$ is divided into morphemes. Then, we extract the nouns $n(1, \ldots, n, \ldots, N)$. For each noun $n$, a normalized histogram $hn$ is created by counting the number of times the noun $n$ is contained in page $u$, followed by normalization throughout the pages. In other words, each bin $bu,n$ of the histogram $hn$ represents how many times page $u$ contains noun $n$. Note that the bins are normalized after counting the number of times noun $n$ appears in all the pages.

Figure 2 shows an example of a noun histogram when the following quiz statement is provided.

**Quiz:** “What is the smallest element constituting a digital image?”

The horizontal axis and vertical axis of Figure 2 denote the page number and normalized histogram value, respectively. Five nouns are extracted from the quiz statement, and there are 41 pages of related material. It seems that the higher frequencies are concentrated around page #3.

To acquire the final mining result, the frequencies of all nouns are summed. We define the normalized value $ru$ as the related score of page $u$. Figure 3 shows the related scores calculated from the noun histogram shown in Figure 2. The highest related score is observed for page #3, which is the page manually selected by the teacher.

**Review Page Summarization**

Although the mining method introduced in the above section finds pages that are highly related to a given quiz statement, the relationships among pages are not considered. In other words, a page is individually evaluated whether it contains related nouns or not. To support effective review by students, it is important to provide not only the most related page but also its associated pages. In addition, it is important to customize the review pages according to each student’s particular situation.

In our study, we make the following assumptions to create review material that is adapted for a student’s background.

**All students:** Pages that include similar topics are helpful in supporting students’ review study.

**Individual student:** Pages that were not previewed by a student should be important for the student’s review study.
To generate review material that satisfies the above assumptions, we propose a page-rank-based review summarization method. We call this the SummaryRank (SR) method, which assigns a ranking score to each page. The higher the ranking score of page $u$, the more important the page is for the student. The idea for the proposed SR method is inspired by PageRank (Page et al., 1999) and VisualRank (Jing and Baluja, 2008). When we find that page $u$ is related to a given quiz, and that it relates to page $v$, page $v$ is also important, since page $u$ is important.

**SR** is iteratively defined by the following formula:

$$SR = \alpha (S \ast SR) + (1 - \alpha)E,$$

(1)

where $S \ast$ is the column normalized similarity matrix $S$, in which $Su,v$ measures the page similarity between pages $u$ and $v$. $E$ is a bias vector to impact to the ranking. The details of the methods used to acquire $S$ and $E$ are given in the following subsections. SR is repeatedly updated until it converges. $\alpha$, ($0 \leq \alpha \leq 1$) controls the balance between the similarity matrix and the bias vector. According to the literature (Jing and Baluja, 2008), $\alpha > 0.8$ is often used in practice.

To measure the similarity between all the possible page pairs, we must define a metric. In this study, we simply evaluate the similarity using the L2 norm between two feature vectors:

$$Su,v = \|du - dv\|,$$

(2)

where $du$ and $dv$ are feature vectors represented by a collection of words (Zhang et al., 2010), and $Su,v$ is an element of the similarity matrix $S$. The role of the bias vector is to emphasize a focus page to attain a higher ranking. In our study, a bias vector is generated by considering two aspects.

- **Relation to quiz**: A large bias value should be given to a page if the page has a higher relation to a given quiz.
- **Preview achievement**: A large bias value should be given to a page if the page was not previewed by a student.

Due to the page limitation, we skip the detail calculation of these bias vectors, but they are finally fused to be $E$.

**Experiments**

We investigated the effectiveness of the proposed method in a series of information science classes. In total, 105 first year students, including both arts and science students, attended the classes, which commenced in April 2015. The classes were conducted over 8 weeks. Every week, prior to the beginning of the lecture, we conducted a short quiz to check the level of understanding. There were 25 quizzes in total over the 8 weeks divided into subsets according to the progress of each lecture series.

**Related Page Mining Accuracy and SummaryRank Efficiency**

In this section, we report the results of our investigation of related page mining. Teachers provided the one-to-one correspondence between a quiz statement and its related page in advance. We treated this correspondence as Ground Truth, and evaluated the top ranked matching rates. Figure 4 shows the cumulative matching characteristic (CMC) curve, which measures how well the proposed method ranks the desired page with respect to a given quiz statement. The curve denoted “PageMining” represents the related page mining results reported in section. The proposed method showed higher accuracy in locating related pages. The curve denoted “SummaryRank” represents the result when we ignored the bias vector relating to preview achievement, which strongly depends on the individual student. The proposed summary rank algorithm finds pages that include similar topics to the page most closely related to a given quiz statement. Therefore, there is a possibility that the
desired page will be ranked after the convergence of the SR algorithm, even if it is not included in the results of related page mining. There were five cases in which the desired pages were not found by related page mining (denoted “PageMining”). After performing SR, the desired pages were salvaged in three of these five cases. In Figure 4, although the rates for the rank-5 pages were slightly lower than those of PageMining, SR achieved a higher recall rate in the rank-10 matching. Based on these results, we found that the proposed SR approach provides better performance in terms of finding pages related to a given quiz statement.

Figure 4: Cumulative Matching Characteristic (CMC) Curve. The “Pv. XX%” means students’ preview achievement rate.

Personalized Review Material
In this section, we investigate the results of review materials, which are realized by introducing the preview status of each student. By analyzing e-Book action logs, we were able to ascertain the page at which a student stopped previewing the material. The bias vector $EP$ is calculated by the achievement rate of each student, that is why the review material is personalized. Due to the page limitation, we show a typical result of personalized review material consisting of 10 pages in Figure 5. For comparison, the result of related page mining (SummaryRank is not applied) is shown in the most left column. The remaining columns represent three kinds of summarized review materials. SummaryRank(Pv. 0%), SummaryRank(Pv. 30%), SummaryRank(Pv. 70%) are personalized review materials for students whose preview achievement was 0% (No preview), about 30%, and about 70% respectively. Note that we selected the paged ranked in top-10 (i.e., most reliable 10 pages), then sort the pages by the page numbering. In the figure, each page is surrounded by colored rectangle. The red color denotes the key page matched to Ground Truth. In all review materials, the most important page is contained. The green color represents pages related to the key page. These pages are helpful for students to understand the key page. Finally, the blue color means the pages which were not previewed by the students. Based on the preview achievement, the summarized review materials differ from each other. In the case of SummaryRank(Pv. 0%), the related page are surrounded by blue rectangles because the students did not preview these pages.

Conclusion
In this paper, we proposed a method to create a summary set of lecture slides to support students’ review activity. First, a quiz statement is analyzed to extract the nouns. Then, text mining is performed to find pages in the lecture materials related to the given quiz statement. The proposed SummaryRank algorithm evaluates the topic similarity among the 4 pages found in the previous step. In addition, our proposed method considers the preview status of individual students, enabling the creation of adaptive review material customized for each student. In the experiments, the proposed method could find appropriate pages with respect to the quiz statements. Further, we confirmed that the adaptive review material for each student is automatically generated by referring to the preview logs provided by the e-Book system. In future work, we will provide summarized review material to students and investigate whether or not this material is effective in enhancing understanding of the lecture. Further, a comprehensive support system will be developed by combining the summarization system for preview material proposed by Shimada et al. (2015) and that for review material proposed in this paper.
Figure 5: Examples of personalized review material. The most left column is the result of related page mining. The second, third and forth columns are Summary Rank results with respects to preview status of students. The order of each column is sorted by page numbering (it is not the ranking order). The red, green and blue rectangles denote the key page matched to Ground Truth, pages related to the core page and not-reviewed pages respectively.
Acknowledgements
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References


Learning Activity Features of High Performance Students

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Abstract: In this paper, we present a method of identifying learning activities that are important for students to achieve good grades. For this purpose, the data of 99 students were collected from a learning management system and an e-book system, including attendance, time on preparation and review, submission of reports, and quiz scores. We applied a support vector machine to these data to calculate a score of importance for each learning activity reflecting its contribution to the attainment of an A grade. Selecting certain important learning activities by following several evaluation measures, we verified that these learning activities played a crucial role in predicting final student achievements. One of the obtained results implies that time on preparation and review in the middle part of a course influences a student’s final achievement.

Keywords: learning analytics, data of LMS and e-book system, learning activity feature, support vector machine

Introduction
In recent years, intensive data mining in the field of education research has become possible, as the widespread use of ICT-based educational systems, such as learning management systems (LMSs) and e-book systems. These systems enable us to automatically collect many kinds of log data that corresponding to students’ online learning activities. Such collected data can be analyzed in order to identify the students’ learning activities and typical learning patterns of particular target students or groups, for example, those who are likely to fail or drop out of class, commonly referred to as “at-risk” students (Baradwaj & Pal (2011)).

In October 2014, the well-known LMS Moodle and the e-book system BookLooper(1), provided by KYOCERA MARUZEN Systems Integration Co., Ltd., were introduced at Kyushu University in Japan in order to facilitate the collection and analysis of educational data. The e-book system records detailed action logs with the user id and timestamp, such as moves back and forth between pages, the contents of memos, and the kind of access device used (PC or smartphone). These records enable us to investigate a range of learning activities, both inside and outside of class. Utilizing the log data stored in Moodle and BookLooper, a number of investigations have been conducted at Kyushu University (Ogata et al. (2015)).

Several studies on educational data mining have some specified measures of learning activities that are utilized for visualizing and analyzing students’ learning behaviors. For example, in Okubo et al. (2015), it has realized to visualize the four types of learning logs stored in an LMS and an e-book system, namely attendance, time spent for browsing slides in an e-book system, submission of reports and quiz scores, by using a discrete graph for each academic achievement, referring to the method proposed in Hlosta et al. (2014). On the other hand, You (2016) has claimed that researchers ought to identify meaningful learning activities to predict students’ achievement. They have verified significance of particular learning activities by the statistical analysis methods. Focusing on methods of analysis, Ifenthaler and Widanapathirana (2014) showed case studies of educational data mining utilizing the well-known method of machine learning, namely support vector machines (SVMs) introduced in Cortes & Vapnik (1995). Goda et al. (2013) applied an SVM to students’ comments and showed the relationships between self-evaluation comments and the final grade of the students.

In this paper, we propose a method of discovering learning activities that are important for students to achieve good grades, by applying SVM to log data stored in an LMS and an e-book system. For this purpose, we use four types of learning logs, namely, attendance, slide browsing time, submission of reports and quiz scores. We verify the performance of prediction of student’s final achievement on the basis of only certain learning activities selected as important by our method. We also discuss an interpretation on learning activities selected as important by our method. Finally, we give an indication of future research plans along the same line as the research presented in this paper.
Method

Data collection
We collected the learning logs of 99 students attending an “Information Science” course that started in October, 2014. The course was held over 14 weeks, with a cancellation in the 9th week; thus, 13 lectures were given. Each of these lectures was presented by using several slides in the e-book system, with each slide associated with only one lecture. The slides were used by the students to complete their preparation and/or review sessions before and after each lecture, respectively. Furthermore, the students were required each week to submit a report and answer a quiz that contained three to five questions related to that week’s lecture through the LMS.

As mentioned above, we refer to four kinds of data stored in the LMS and the e-book system in this paper, namely

- attendance or absence (represented by p),
- submission of a report or failure to do so (r),
- a sum of the time spent browsing slides for preparation and/or review (b), and
- quiz score (t),

of each student participating in each week of the course. For each of the four items, we consider whether or not it was achieved. Thus, for the i-th week, a particular student’s lecture attendance or absence is coded by the word ip:o or ip:x, respectively. Each student’s report submission datum was coded as ir:o if a report was submitted and ir:x if not, respectively. Slide browsing time was also transformed into a binary category, with browsing time of 600 seconds or longer coded as ib:o, and anything shorter as ib:x. Similarly, a quiz score of 70% or above was coded as it:o, and anything lower as it:x. For example, if a student in the 7th week attended a lecture, did not submit a report, browsed slides for longer than 600 seconds, and scored below 70% on the quiz, the words 7p:o, 7r:x, 7b:o, and 7t:x would represent this student’s activities in the 7th week.

We note that the data on the activities of each student in the class can be represented by an 8*14=112-dimensional vector, in which each element is either 0 (for ip:x, ir:x, ib:x, and it:x) or 1 (for ip:o, ir:o, ib:o, and it:o).

The students in the course were graded in terms of the categories A, B, C, D, and F according to their grade score out of 100, which reflected all their activities. The relationship between grade and grade score is indicated in Table 1, which shows the frequency with which the 99 students attained each grade. The words s:A, s:B, s:C, s:D and s:F were used to represent the log data of these grades.

By registering the data of the 99 students as documents, we constructed a search engine by means of GETA2(Generic Engine for Transposable Association) provided by National Institute of Informatics.

<table>
<thead>
<tr>
<th>Grade</th>
<th>Grade score range</th>
<th>Number of students</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>90-100</td>
<td>37</td>
</tr>
<tr>
<td>B</td>
<td>80-89</td>
<td>30</td>
</tr>
<tr>
<td>C</td>
<td>70-79</td>
<td>13</td>
</tr>
<tr>
<td>D</td>
<td>60-69</td>
<td>9</td>
</tr>
<tr>
<td>F</td>
<td>0-59</td>
<td>10</td>
</tr>
</tbody>
</table>

Classification based on SVM and feature selection
The aim of this study is to discover important learning activities that distinguish students achieving A grades from students achieving lower grades. For this purpose, we utilized an SVM in which the documents of A grade students are positive instances and the documents of students with other grades are negative instances. Following the method proposed in Sakai & Hirokawa (2012), we applied machine learning method based on SVM and feature selection to classify students’ learning activities data.

An evaluation of classification performance of the proposed method is conducted by means of 5-fold cross validation. Thus, the data are separated into five parts, of which four parts are used as training data and the remaining part as test data. Then, there are five ways to choose the parts for training data and test data. Thus, the final result of such 5-fold cross validation is the average of the results of these five ways.

Specifically, our method is conducted in terms of the following steps.

Data generation by multiple instance method
The collected data consisted of 37 positive instances and 62 negative instances. As the number of instances in the training data is somewhat small, we attempt to apply a restricted version of multiple instance learning
(Dietterich et al. (1997)). Specifically, from the training data, we randomly choose a pair of positive instances, and regard this pair as a new positive instance (called a “bag” in Dietterich et al. (1997)). In this way, we construct new 100 positive instances. Similarly, 100 new negative instances can be constructed. By adding these new instances to the original training data, we can increase its volume.

**Application of linear SVM**
Applying linear SVM to the training data containing all words, we construct the model that classifies the documents of A grade students. We used SVM-light for the learning tool.

Recall that a document of a student is represented by a 112-dimensional vector. For a word $w$ and a document $d$, the number of occurrences of $w$ in $d$ is denoted by $tf(w, d)$, which equals either 0 or 1. The classifier (or model) $f$ of the linear SVM learned from the training data is of the form

$$f(d) = \sum_{w \in d} \text{weight}(w_i) \cdot tf(w_i, d) + b,$$

where $b$ is a constant term. For a document $d$ of test data, if $f(d)$ is greater than 0, then $d$ is classified as a document of grade A student. Conversely, if $f(d)$ is less than 0, then $d$ is classified as a document of a student with another grade.

**Score of word and feature selection**
For a given word $w_i$, its $\text{weight}(w_i)$ can be regarded as a score of importance of $w_i$ on the classifier $f$. A score of importance of $w_i$ can be obtained by applying $f$ to a document containing only $w_i$ and removing the constant $b$.

Feature selection of words is conducted by following the six measures for evaluation, shown in Table 2, in which the number of documents containing $w$ is denoted by $df(w)$ and an absolute value of $x$ is denoted by $\text{abs}(x)$. For $N=1, 2, ..., 10, 20, ..., 70$, we choose the top $N$ positive words and top $N$ negative words regarding each measure of $w.o$, $d.o$, and $l.o$. Similarly, we choose the top $2N$ words regarding each measure of $w.a$, $d.a$, and $l.a$. These $2N$ words are called feature words of $f$.

We apply linear SVM to the training data which containing $2N$ words selected by the six type of feature selection and to the training data of all words. Then, using the test data, we evaluate an estimation performance of each model obtained by the linear SVM, by means of 5-fold cross validation.

**Table 2: Measures for feature selection**

<table>
<thead>
<tr>
<th>Type</th>
<th>Measure for evaluation</th>
</tr>
</thead>
<tbody>
<tr>
<td>$w.o$</td>
<td>$\text{weight}(w_i)$</td>
</tr>
<tr>
<td>$d.o$</td>
<td>$\text{weight}(w_i) \cdot df(w_i)$</td>
</tr>
<tr>
<td>$l.o$</td>
<td>$\text{weight}(w_i) \cdot \log(df(w_i))$</td>
</tr>
<tr>
<td>$w.a$</td>
<td>$\text{abs}(\text{weight}(w_i))$</td>
</tr>
<tr>
<td>$d.a$</td>
<td>$\text{abs}(\text{weight}(w_i) \cdot df(w_i))$</td>
</tr>
<tr>
<td>$l.a$</td>
<td>$\text{abs}(\text{weight}(w_i) \cdot \log(df(w_i)))$</td>
</tr>
</tbody>
</table>

**Experimental results**

**Accuracy**
We have conducted experiments to obtain the values for accuracy, precision, recall, and F-measure as evaluation indexes for each model obtained by the linear SVM for

- all words, and $2N$ selected words with $N=1, 2, ..., 10, 20, ..., 70$, and
- the six types ($w.o$, $d.o$, $l.o$, $w.a$, $d.a$ and $l.a$) of feature selection.

Figure 1 illustrates the relationship between the accuracy of each model obtained by the linear SVM and the value of $N$. The vertical axis represents for accuracy, and the horizontal axis is for the number of selected words $N$. The baseline represents the accuracy of the model by using all words.
In the case of the model using all words, the accuracy was 0.7358. On the other hand, when \( N=6 \), applying feature selection \( w.o \), the accuracy was 0.8853, which was the best score of all models. Thus, it seems that an appropriate feature selection based on linear SVM may be effective in reinforcing the estimation performance.

The scores for precision, recall, F-measure, and accuracy of the five models with the best scores are summarized in Table 3.

Table 3. The top five models and their precision, recall, F-measure, and accuracy scores.

<table>
<thead>
<tr>
<th>Type of FS</th>
<th>N</th>
<th>precision</th>
<th>recall</th>
<th>F-measure</th>
<th>accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>( w.o )</td>
<td>6</td>
<td>0.7000</td>
<td>1.0000</td>
<td>0.7976</td>
<td>0.8853</td>
</tr>
<tr>
<td>( d.a )</td>
<td>4</td>
<td>0.7033</td>
<td>1.0000</td>
<td>0.8148</td>
<td>0.8470</td>
</tr>
<tr>
<td>( w.o )</td>
<td>8</td>
<td>0.7286</td>
<td>1.0000</td>
<td>0.8359</td>
<td>0.8300</td>
</tr>
<tr>
<td>( l.a )</td>
<td>9</td>
<td>0.6451</td>
<td>1.0000</td>
<td>0.7641</td>
<td>0.8224</td>
</tr>
<tr>
<td>( w.o )</td>
<td>9</td>
<td>0.6803</td>
<td>1.0000</td>
<td>0.8092</td>
<td>0.8139</td>
</tr>
</tbody>
</table>

Feature word
For the case of \( N=6 \), applying feature selection by \( w.o \), we summarize the top six positive feature words and the top six negative feature words and their scores of importance in Table 4.

For example, the presence of the 12th week was the most influential learning activity in obtaining an A grade, and preparation and/or review of the 6th week was the most influential in failing to achieve an A grade.

We notice that 11b:o is the second positive feature words, while 11b:x appears as the third negative feature word. Thus, it can be suggested that preparation and/or review of the 11th week significantly distinguished A grade students from other students. In this “information science” course, the learning contents for the 11th week was bucket sort and binary search. It may therefore be supposed that

- these contents were the basis of other contents in the following weeks, or
- these contents were included in the final examination and were sufficiently important to classify the students’ grades.

Focusing on negative feature words, the top three words were of the form 1b:x, reflecting less than 600 seconds of slide browsing time of for preparation and/or review. The top three negative words shown that, in the middle part of the course, the students who neglected a preparation and/or review missed achieving an A grade. This result suggested that it may be important for a teacher to guide students in continuing to prepare for and review lectures through out the course, until the last week, in order to maximize their achievement.

These feature words may be used for two purposes. First, after finishing the course and grading the students, a teacher can tell the students which learning activities were not sufficient to obtain a good grade. Second, if a teacher is to conduct a similar course in the future, he/she can call students’ attention to the learning activities indicated by positive feature words, and advise them to avoid learning activities indicated by negative feature words.
Table 4. The top six positive and negative feature words for N=6.

<table>
<thead>
<tr>
<th>Positive</th>
<th>Negative</th>
</tr>
</thead>
<tbody>
<tr>
<td>Word</td>
<td>Score of word</td>
</tr>
<tr>
<td>12p:o</td>
<td>0.4554</td>
</tr>
<tr>
<td>11h:o</td>
<td>0.4480</td>
</tr>
<tr>
<td>10r:o</td>
<td>0.3223</td>
</tr>
<tr>
<td>11r:x</td>
<td>0.2871</td>
</tr>
<tr>
<td>5b:o</td>
<td>0.2686</td>
</tr>
<tr>
<td>8p:x</td>
<td>0.2415</td>
</tr>
</tbody>
</table>

Course grade scores vs. predicated A-score
For the case of N=6, applying feature selection by w.o., we let f₁, f₂, ..., f₅ be the classifiers of linear SVM, learned during the 5-fold cross validation. Then, we define the predicated A-score pr(d) of a document d of a student as the average of f₁(d), f₂(d), ..., f₅(d).

For each student, we compared the grade score with the predicated A-score. The results are summarized in Figure 2, in which the vertical axis shows the predicated A-score, and the horizontal axis the grade score.

We can observe that there is a positive correlation between grade score and predicated A-score. Specifically, the correlation coefficient of them is 0.6333. Thus, it can be said that this model regarding whether or not students obtain an A grade is appropriate to discuss students’ grade scores.

Figure 2. Course grade score vs. predicated A-score

Conclusion
In this paper, we proposed a method by which learning activities important for attaining high achievement in a course may be identified by using learning logs stored in an LMS and an e-book system. These logs contain the following four items, namely, attendance, slide browsing time for preparation and/or review, submission of reports, quiz scores, and grades. The learning activities of the students in a course can be represented by a vector that reflects achievement or non-achievement of each of the above four items in each week. In our method, first, linear SVM is applied to these vectors and a score of importance for the contribution of each learning activity to students’ attainment of an A grade is calculated. Following this, we select N activities that have the best and worst scores of importance by following the six measures for evaluation. We then apply linear SVM to the data that consists of only the selected activities to verify that these activities are sufficient to infer a student’s final achievement.

We applied this method to the data from 99 students attending an “Information Science” course. In the case of N=6, and applying feature selection w.o., the accuracy of prediction by using linear SVM was 0.8853, which was the best score of all constructed models. On the other hand, in the case of using of all learning activities, the accuracy was 0.7358. Hence, feature selection based on linear SVM appears to be effective in
reinforcing the estimation performance. The selected activities were shown in section Table 3. From these results, we can observe that (i) preparation and/or review in the 11th week significantly distinguished A grade students from other students, and (ii) students who neglected preparation and/or review in the middle part of the course were unlikely to obtain an A grade. Furthermore, for each student, we compared the grade score with the predicated A-score by linear SVM with N=6, applying feature selection w.o. The correlation coefficient of them was 0.6333. Thus, it seems that the model regarding whether or not students obtain an A grade is appropriate in discussing the grade scores of students.

These results can be informative in telling students which learning activities were insufficient to obtain a good grade, and in advising students in following years of the same course on the important learning activities. A number of issues remain to be investigated. Points of particular importance includes the following:

- More data from additional courses is required to support the present conclusions. It may be also interesting to compare the results of this study to data from another course.
- In our method, the thresholds for the achievement of slide browsing time for preparation and/or review and quiz scores were decided manually by the authors with no justification. It is important to determine the most suitable thresholds for identifying the specific features of the learning activities of high achieving students, automatically.
- By using our method, we can discover important learning activities for a good achievement. However, the reasons why these learning activities are selected by the model are not so easy to understand. Analysis of the relationships among learning activities, such as associations analysis, may help to interpret the present results further.

Endnotes
(1) http://booklooper.jp
(2) http://geta.nii.a.c.jp
(3) http://svmlight joachims.org/

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Acknowledgments
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Learning Pulse: Using Wearable Biosensors and Learning Analytics to Investigate and Predict Learning Success in Self-regulated Learning

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Abstract: The Learning Pulse study aims to explore whether physiological data such as heart rate and step count correlate with learning activity data and whether they are good predictors for learning success during self-regulated learning. To verify this hypothesis an experiment was set up involving eight doctoral students at the Open University of the Netherlands. Through wearable sensors, heart rate and step count were constantly monitored and learning activity data were collected. All data were stored in a Learning Record Store in xAPI format. Additionally, with an Activity Rating Tool, the participants rated their learning and working experience by indicating the perceived levels of productivity, stress, challenge and abilities along with the type of activity. These human annotated labels can be used for supervising machine learning algorithms to discriminate the successful learning moments from the unsuccessful ones and eventually discover the attributes that most influence the learning process.

Keywords: Learning Analytics, Biosensors, Affective Computing, Wearable Enhanced Learning

Introduction
This paper presents the development of Learning Pulse, a study designed and conducted within the Technology Enhanced Learning Innovations (TELI) department of the Welten Institute, a research centre at the Open University of the Netherlands. Learning Pulse, funded via the Learning Analytics Community Exchange project7, is a research initiative of the Learning Analytics and the New Learning Experience thematic working groups of TELI in cooperation with the Department of Data Science and Knowledge Engineering (DKE) of Maastricht University. The study took place from September to December 2015 with the idea to combine wearable technologies with learning activity data in order to analyse and empirically infer the learning patterns of an individual by means of machine learning, data mining and information visualisation techniques. The approach used in Learning Pulse is an example of learning analytics tailored to bridge physical with digital learning spaces (CrossLAK theme 2) and of combining data from varied heterogeneous data sources (CrossLAK theme 4) by means of the new xAPI data standard.

Rationale
Learning Pulse aims at modelling the endeavours of an individual learner in the context of self-regulated learning or cognitive work. Thus, there are three main assets that constitute the study: (1) the employment of biosensors to collect physiological data, (2) the use of regular subjective activity reporting and, (3) the use of predictive and learning platform independent learning analytics. The context and the three research assets are hereby described.

Self-regulated Learning
Self-regulated learning is the process whereby learners set goals for their learning and monitor, regulate, and control their cognition, motivation, and behaviour, guided and constrained by their goals and the contextual features of the environment (Pintrich & Zusho, 2007). The first important assumption that holds for a self-regulated learner is the strong engagement with the learning activity and the desire of improving the learning

7 http://www.laceproject.eu
performance (Butler & Winne, 1995). Learning Pulse builds on this natural desire and aims at developing a model to support this disposition. The second assumption is that each individual learns differently and has his/her own goals, cognition and motivation (Ryan & Deci, 2000). The predictive models, which will be described later, will therefore be specific and valid only to one specific learner.

Biosensors for Learning

Biosensors are getting increasingly available to the general public: embedded in wearable technologies, biosensors are more and more being used in industries like healthcare, fitness, and sports (Swan, 2012). Multi-sensor approaches, combined with cardiovascular activity, are also a growing trend in the industry (Schneider et al., 2015). Such involuntary responses are easier and cheaper to measure but more difficult to interpret, being the result of a complex system of stimuli (Pijeira-Díaz et al., 2016). The role of the physiological footprints over psychological states has been subject of research for several decades and has already offered interesting insights. Boucsein & Backs (2000) for example relate significant change in physiological responses to common physical and mental activities. Among all physiological responses heart rate is accounted to be the most recurrent and thus most predictive one. In related research there is, however, little focus on the role that biosensors have in enhancing learning (Schneider et al., 2015). Learning Pulse aims to address this challenge, researching for meaningful patterns in physiological responses in self-regulated learning.

Predictive Learning Analytics

The process of exploiting learning data with the aim of understanding and thus optimising the learning practice is usually referred to as learning analytics (LA). Consisting of several different disciplines including learning science, software engineering, statistics, data mining and information visualisation, LA is a modern and powerful tool for sense-making of educational data (Siemens & Baker, 2012). In particular, the capacity to make predictions on learning outcomes makes learning analytics highly valuable for all stakeholders in education (ECAR-ANALYTICS Working Group, 2015). A common drawback on the application of LA is to limit the scope of the learner’s activity only to one specific virtual learning environment (VLE) or learning management system (LMS). However, as Suthers & Rosen (2011) point out, learning is often distributed across multiple media, websites and networked environments; the learning activity traces may be fragmented and not match analytic needs. Learning Pulse aims to address this issue by employing platform-independent learning analytics: instead of looking at a particular application or environment, it logs the use of all software in use during the learning activity.

Method

The overarching research question is given below, followed by a possible follow-up question if question 1 is answered positively. This second research question seeks to understand if, by leveraging biosensor data, by scoring and predicting learning success and by constantly feeding back these predictions to the learner, the learning and the cognitive work performance will eventually increase.

1. Are physiological responses like heart rate and step count, when associated with learners’ activity data, predictive for learning and cognitive working performance?

2. Can biofeedback techniques be employed to improve learning and cognitive working performance?

In Learning Pulse the hypothesis range is thus defined by the degree of success in the learning activity. As first theoretical ground for learning success, the concept of Flow is used. Theorised by the Hungarian psychologist Csikszentmihalyi, the Flow is a mental state of operation that an individual experiences when immersed during a state of energised focus, enjoyment and full involvement in the activity process. Being in the Flow means feeling in complete absorption with the current activity and being fed by intrinsic motivation rather than extrinsic rewards (Csikszentmihalyi, 1997). According to Csikszentmihalyi, the Flow happens whenever there is a balance between the level of difficulty of the task (the Challenge dimension) and the level of preparation of the individual for the given activity (the Abilities dimension). When these two dimensions are maximised, the Flow is likely to manifest.
Experimental Setup and Task Description

The experiment lasted twelve working days and involved eight participants, four males and four females, aged between 25 and 35, all of them doctoral students at the TELI group of the Open University of the Netherlands with backgrounds in different disciplines including computer science, psychology and learning science. Being PhD students, they can be considered both learners and cognitive workers. To carry out their own research, the participants used their personal laptops and were asked to install a preconfigured software tracking tool. All participants were also provided with a wearable fitness tracker and were asked to sign an informed consent form about the use of their personal information for research purposes. During the experiment the participants were asked to continue their research activity as usual and, while doing that, rate their learning activity every hour between 8AM and 7PM, for those hours that they worked. The ratings were collected through a web application developed ad hoc, named Activity Rating Tool. In addition, to get more insights into how stressful moments are reflected in the heart rate changes and self-perceived productivity, the participants were asked to do additional tasks, such as delivering presentations or submitting short abstracts about the topic of their research.

Data Sources

Learning Pulse uses four sources of data as detailed below: biosensor data, user activity data, rating data, and weather data. All the collected data are summarised into an Entity-Relation Model shown in Figure 1. Physiological data were collected using Fitbit Charge HR\(^8\), a wristband that every participant wore throughout the whole experiment. A Fitbit is a commercial wireless tracker that embeds different sensors to track a number of statistics in real-time, including heart rate, steps taken, distance travelled, calories burned, stairs climbed and active minutes throughout the day. The two measurements of interest for Learning Pulse are the heart rate and step count, updated respectively every five seconds and every minute. With such frequency the values of these two variables are stored for every participant from 8AM until 8PM during the 12 days of the experiment. The other biosensor, used however for only one participant, observes two measures: skin conductance, updated up to four times every second, and the noise level, updated with the same frequency. The values of this sensor are directly stored in the Learning Record Store in xAPI format (see below).

The activity data was obtained using RescueTime\(^9\), a time management software meant to be a working efficiency tool. RescueTime can be installed on different platforms and generates personal analytics by logging the applications running on the laptop or mobile device. Every five minutes, RescueTime stores an array containing the applications in use, weighted by their duration in seconds, into a proprietary cloud database. Each application is also given a category.

The users' ratings were collected through the Activity Rating Tool, a web application developed in Python running on Google App Engine server. When a user accesses the app and authenticates into the system, he/she is able to click onto one of the past learning intervals (timeframe) of that current day. To simplify the data collection process, the timeframes to be rated have a fixed length of one hour: they begin and end at full hours (e.g. the first timeframe goes from 8AM to 9AM). To rate the activity each participant is asked first of all to choose, from a closed list, the category of the main activity performed during the selected timeframe: (1) reading, (2) writing (e.g. a paper, or a presentation), (3) meeting (both online, offline), (4) communicating (with email, or chat), or (5) other (e.g. going to lunch, having a break). Then, through a sliding button, a value ranging from 0 to 100 has to be chosen for each of the following questions:

- Productivity: How productive were you?
- Stress: How stressed did you feel?
- Challenge: How challenging was the activity?
- Abilities: How prepared did you feel for the activity?

In order to make the ratings as accurate as possible, at the end of each timeframe, participants were encouraged to rate their activities directly after a timeframe concluded by an email reminder to the personal inbox of each participant. All the ratings were stored in Google Datastore and sent in xAPI format to the Learning Record Store as detailed in the section 3.4.

Weather condition may also have an influence on individual learning performance. For this reason it has been decided to model the weather as an extra feature of the learning process. The web service

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\(^8\) https://www.fitbit.com/chargehr
\(^9\) https://www.rescuetime.com
Weather Underground\textsuperscript{10} was chosen for providing free historical weather data. Updated every 30 minutes, the weather data consist of four attributes: temperature, pressure, humidity, hourly precipitation.

Data Collection
To support the collection of such heterogeneous types of data, Learning Pulse uses a flexible software architecture. In Figure 2 all the different components are divided in three functional layers: (1) the Application Layer, (2) the Controller Layer, and (3) the Data Layer.

The Application Layer is constituted by the user interfaces, the sensors and the third-party applications which the user directly interacts with. The components of this layer are responsible for collecting the data of the environment and sending them to the Controllers. In this layer fall the Activity Rating Tool, the Fitbit tracker, the skin-conductance sensor and the RescueTime software. The Controller Layer is the core of the software architecture responsible for the processing, manipulation and storing of the data collected. It includes the server-side web application of the Activity Rating Tool, the management of the user accounts, and the data-importing mechanisms to gather the data from the third-party datastores. Part of the Controllers is also the Data Transformer, which prepares the data in the correct representation. The Data Layer is the layer where all the data reside. It includes both the internal databases, i.e. the Dataseore and the Learning Record Store, and the third party cloud datastores such as the Fitbit and RescueTime ones.

Data Storing
The standard chosen to store Learning Pulse data is the Experience API (xAPI). The xAPI is an open source API and RESTful web service, with a flexible standard based on learning statements with the format actor-verb-object. The statements, generated in JSON format, are validated by and stored in a Learning Record Store (LRS). The main advantage of xAPI is interoperability: learning data from any system or resource can be captured and eventually queried by third-party authenticated services. In Learning Pulse xAPI statements are opportunely designed: to store for example one heart rate value for the user ARLearn7, the xAPI statement will carry the following meaning “At timestamp 2015-11-24 08:05 ARLearn7 experienced Heart-Rate of value 87”.

One statement is hence generated for every sensor at any value update. This results in a considerable size of information to be stored. To handle the load of information the Learning Record Store is implemented with Google Big Query Datastore, a non-relational and highly scalable datastore which is able to query massively large datasets in few seconds.

Hypothesis Modelling
A graphical representation of Csikszentmihalyi’s model is given in Figure 3. Having sampled, through the Activity Rating Tool, Challenge and Abilities as normalised numerical values the Flow can be calculated as follow:

\textsuperscript{10} http://www.wunderground.com
where $F_{ij}$ is the Flow score for the learner $i$th at the timeframe $j$th; $A_{ij}$ and $C_{ij}$ are the values rated by the learner $i$th at the timeframe $j$th for, respectively, level of Abilities and Challenge. In the scatter plot in Figure 4 the ratings of one participant are plotted in a two dimensional space and are coloured depending to their value of Flow calculated with formula (1).

To check the validity of the hypothesis, the flow score will be validated by computing its correlations with productivity and stress, in order to check if increasing flow corresponds to increasing productivity and stress. The use of the Flow score enables a representation of the “learning success” of an individual at a particular point of time as a single normalised value. Maximising this value will therefore mean maximising learning success. To further simplify the number of hypothesis, the range of Flow score is divided into three sections: (1) Low success where $0 < F_{ij} \leq 0.33$; (2) Medium success where $0.33 < F_{ij} \leq 0.66$; and (3) High success where $0.66 < F_{ij} \leq 1.00$. The traffic-light classification is popular in the field of predictive learning analytics since it is straight-forward to understand (ECAR-ANALYTICS Working Group, 2015).

**Analysis and Further Steps**

Once the language of hypothesis is defined, the next step consists of defining the language of learning samples, or in other words, devising a representation of the data convenient for the regression task – i.e. predict the correct Flow class. Given that the data present several one-to-n relations, a suitable representation would be a multiple-time-series in which every data point is a five-minute discretised interval. With such representation each observation can be seen as a stochastic process governed by a set of equations, each of them explaining the previous observations and being of order equal to the number of attributes considered. An expected example of the correlations among the observations can be the following: having a lunch break or a walk is likely to influence the productivity of the next hours. Assuming that there is dependence among the observations restricts the range of possible regression models that can be used. With the choice of regression model other issues need to be addressed. When opting for the five-minute interval representation, those attributes having more than one value every five minute (heart rate above all) need to be represented in a way to avoid information loss. Also the dimensionality can constitute a considerable challenge: events that occurs seldomly, like the use of a particular software application, will turn into very sparse signals presenting few spikes but most of the time zeros.

Finally, once a good performing regression model is trained to discriminate learning success, it can be exploited to make predictions almost in real time. This means for example being able to predict whether the next five, ten minutes or even one hour, is likely to be the time for a successful learning experience. This predictive capability will be explored also in further studies, i.e. *Visual Learning Pulse*, using dashboards to display feedback to the learner.
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Opening the Black Box of Practice-Based Learning: Human-Centred Design of Learning Analytics

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Abstract: Practice-based learning activities are an important aspect of education, particularly for science, technology, engineering and mathematics (STEM) subjects. Their immense importance to STEM curricula is unequivocal and so are the teachers’ and students’ need for support during those activities. However, considering the open-ended and hands-on nature of practice-based learning activities, designing, deploying and validating learning analytics visualisations remains as a significant challenge for the state-of-the-art learning analytics. In this paper, we present our human-centered contextual enquiry approach for generating requirements and its preliminary results in the form of visualisations that have the potential to support facilitators and learners. Although there have been certain attempts to provide learning analytics for increasing awareness, supporting reflection and facilitating decision-making and intervention, to our knowledge, our research presented is the first attempt to provide such information regarding students’ progress during practice-based learning activities.

Keywords: practice-based learning, contextual inquiry, learning analytics, feedback, visualizations

Introduction and Background
In STEM teaching, practice-based learning is considered to be an essential part of teaching and learning (Millar, 2004). Guidance is essential in those activities (Clark, 2009), since allowing students to work independently does not always lead to meaningful learning outcomes (Cukurova & Bennett, 2014). Facilitators of practice-based learning activities, as well as learners, are in need of tools that can provide them with indicators of learning processes in order to support teacher monitoring and learner self-regulation (Dillenbourg et al., 2011). Yet, little is known about what should be and can be presented to teachers and learners in practice-based learning environments. In this paper, we present our visualisation tool based on the outcomes of a contextual inquiry in practice-based STEM teaching and human-centred iterative design methodology.

Learning Visualizations
A number of visualisation tools have been developed for online, face-to-face, and blended learning settings, where this data is more readily available. Most of these attempts aim to support teachers (Verbert et al., 2014), but some applications have also been developed to support students’ awareness and self-reflection (e.g. (Govaerts, Verbert, Klerkx, & Duval, 2010). Researchers have developed visualisations of students’ access to resources, their communication patterns in forums, as well as frequency and timings of their activities (e.g. (Coffrin, Corrin, de Barba, & Kennedy, 2014). Such visualisations enable teachers to provide better support, for example by identifying patterns of participation and intervening in problematic groups (Van Leeuwen, Janssen, Erkens, & Brekelmans, 2014). Similarly, student learning in intelligent tutoring systems is more easily tracked, and several visualisation tools have been developed to provide students with information on their progress e.g. (Lafford, 2004).

These solutions, however, do not necessarily transfer in open-ended, practice-based learning where the technical challenges are very different and the usability and pedagogical requirements are not yet well understood. First, practice-based learning activities usually take place simultaneously in multiple groups of students, sometimes in a range of physical spaces and across a large time-span. In addition, the diverse set of digital and non-digital activities cannot always be tracked keeping practice-based learning largely out of the scope of current learning analytics trends, despite its immense importance to STEM curricula. We are interested in investigating whether learning analytics can support the challenging role of the teacher or facilitator in such settings and/or help students reflect on their own practice. The challenges teachers face during practice-based learning, particularly in formal education, are well documented.
Teachers are rarely aware of the processes followed by students during these activities (Race, 2001), and it is challenging for them to provide appropriate support to individual students, who have different needs, strengths and weaknesses (Zhang, Zhao, Zhou, & Nunamaker, 2004).

Teachers can only be aware of what a small number of students are doing at any one time in the classroom. It is, therefore, hard for teachers to know which students are making progress, and which are in difficulty and in need of additional support. It is a challenge for teachers to understand the process by which students have arrived at the current state of their practice-based activities and thus to provide appropriate guidance.

**Assistance Tools for Collaborative Digital Learning Environments**

An area with similar challenges, where we have sought inspiration from, is that of teacher assistance or awareness and reflection tools on collaborative or open-ended digital learning environments. Similar to practice-based learning, this requires much more than providing simple descriptive statistics of students’ activities. For example, with the aim of supporting students’ meta-cognitive processes in science and mathematics education the METAforA project developed a bespoke digital platform where students undertake collaborative challenges, describe and enact their plans while working with open-ended environments or games (Dragon et al., 2013). Tracking student activity allows data aggregation and visualization for the teacher in terms of timelines or other charts. Earlier work looked into providing synchronous information to support timely teacher intervention utilising the familiar by now, traffic light metaphor for showing which students are active, inactive or in need of help in an exploratory digital environment for mathematics (Gutierrez-Santos, Geraniou, Pearce-Lazard, & Poulouvasilis, 2012). Roman et al. (2012) explored patterns of collaborative conversation at a non-interactive table aiming to provide information regarding students’ learning process, Martinez-Maldonado et al., (2013) investigated students’ collaborative interactions during their work on an interactive tabletop, Gutierrez-Santos et al. (2012) looked at students’ learning progress and need for help in the context of learning programming and Mercier et al. (2015) studied the collaborative problem solving process within the context of multi-touch technology. Although the aforementioned work points to the potential of tools for increasing awareness, supporting reflection and facilitating decision-making and intervention, to our knowledge, the research presented in this paper is the first attempt to provide information regarding students’ progress during practice-based learning activities.

**Contextual Inquiry into Practice-based STEM Learning**

It is by now well understood that design and evaluation of learning analytics tools targeted at teachers (or facilitators in general) and learners, requires techniques and methods from different disciplines, such as software engineering, human-computer interaction and education (Martinez-Maldonado et al., 2015). As discussed in detail by Martinez-Maldonado et al. (2015), while software engineering or human-computer interaction have a lot of methods to offer in relation to establishing technical or usability requirements and for evaluating systems, they may underestimate the learning context. In our previous experience from participatory design, for example, particularly with teachers, the lack of previous experience on tools that can support decision-making makes it really difficult to elicit requirements (Mavrikis, Gutierrez-Santos, Geraniou, Noss, & Poulouvasilis, 2013). Instead, in such occasions it is necessary to adopt methodologies that appreciate the need of providing participants the opportunity to directly experience a situation and provide meaningful feedback (Mavrikis et al., 2013).

Several methodologies have been used the last few years for designing and evaluating learning analytics tools. One approach that is particularly well suited to our aims is the so-called Learning Awareness Tools User eXperience (LATUX) workflow (Martinez-Maldonado et al., 2015). It was recently put forward as an approach to designing and deploying awareness tools in the classroom by an iterative process of problem definition, low- and higher-fidelity prototypes, pilot studies and validation in-the-wild sessions that can help designers to pay attention to the pedagogical requirements underlying the use of the awareness tools under design. However, even the initial ‘problem identification’ stage requires recognising that in-depth understanding of user behaviour can only be achieved by following a human-centered design process that observes and analyses situations in their actual contexts. This is the main advantage of contextual design approaches or contextual inquiry (Bayer & Holtzblatt, 1998). Hence, in order to understand practice-based learning practices, situate our work in the context of real users and uncover potentials for technology support, we commenced by conducting a contextual inquiry into several STEM learning environments.
Method
Our contextual inquiry was based on the ethnographic method (Hammersley & Atkinson, 1995), combining participative and observational approaches. We visited ten formal educational institutions in four European countries and interviewed 25 STEM teachers and facilitators. We asked questions about the learning environment, the people, spaces and materials involved in the learning process. Each interview lasted for 1.5 to 2 hours and was digitally audio recorded with participants’ permission. The interviews were conducted face-to-face and were later transcribed verbatim for analysis. Additionally, we conducted a total of nine hours of in-situ observations during STEM classes in the same educational environments.

We focused on gaining insights into class dynamics and interaction with learning materials, as well as between peers and teachers within different learning settings. We complemented our data with opportunistic, conversational interviews with a total of 15 students at the end of the observational sessions. Our contextual inquiry was guided by two main research objectives 1) To understand the practices of teachers and learners and their attitude to learning, in the face of material, spatial and logistic constraints and how technological tracing and data analytical augmentation could support them, and subsequently 2) To explore the design of visualizations of practice-based learning activities that can capture aspects of the hands-on, open-ended, collaborative nature of practice-based STEM learning.

Thematic analysis was performed, applying an iterative coding scheme with a mix of both deductive and inductive codes (Braun & Clarke, 2006). The resulting coding scheme included learning activities, motivations and attitudes towards tutoring, assessment and the learning process, challenges, as well as socio-material and socio-spatial relationships between users, materials and spaces in the learning process. While the detailed discussion of thick descriptions of the resulting findings is out of the scope of this paper, in the following we present a summarised set of opportunity areas for research and design of technological data-driven augmentations for practice-based learning.

Findings from the Contextual Enquiry Study
1) **Support Replay and Self-tracking:** Hands-on demonstrations are an often-employed teaching strategy, as teachers believe it is necessary as well as stimulating for students to see the correct step-by-step execution of a hands-on activity (e.g. building a circuit) and comprehend and reflect on the steps behind it. This practice also applies to teachers’ in-class tutoring patterns, which often include conducting hands-on mini-demonstrations with individual groups, live-coding in front of the class to highlight specific problems or error patterns, or ‘reverse engineering’ of students’ current outcome in order to find coding or circuitry problems. However, with several individual groups with different levels of knowledge, it is often difficult (or impossible) to trace their mistakes and ‘replay’ the errors.

2) **Capture and Visualize Programming / Hands-on Issues:** Teachers argue that they often become aware of students’ difficulties during programming and hands-on activities too late, when students are already stuck on larger, more complex issues. They believe they are unable to supervise several student groups simultaneously, and students’ also often lack the motivation and self-regulation skills to identify and report on issues.

3) **Promote and Leverage Documentation:** According to teachers documentation is increasingly integrated in curricula and assessment criteria. Its implementation during the learning process was found as a challenge, yet it is valued. On the other hand, students find it as tedious and make incomplete, unreflective posts. Nevertheless, they enjoy documentation with digital tools (e.g. Facebook).

4) **Support Immediate, Opportunistic Means for Feedback & Documentation:** Documenting can be disruptive to learners - especially in hands-on learning environments. Playful, opportunistic mobile documentation could facilitate the process, complemented by a system that tracks and captures important learning events.

5) **Support Non-linear Tutoring and Orchestration:** Teachers claim that in-class tutoring of hands-on activities is a highly intense and dynamic activity that requires teachers’ attention and engagement at multiple levels. Teachers need to walk around, observe and visit students and attend to their questions and problems, while being able to keep track and give feedback to other students (who sometimes might not even need it). Yet teachers are able to be only at one place at a time, which makes it challenging to attend to specific students’ needs and orchestrate well their feedback. Combining a tracking system that is aware of students’ issues or feedback requests, with on-demand visual feedback through situated, and distributed devices, could provide means to overcome the inevitably ‘sequential’ nature of teachers’ feedback dynamics.
and allow them to prioritise and orchestrate his tutoring scheme.

6) Multi-purpose spaces & dynamics: Students often use school spaces for multiple purposes – such as the workshop for brainstorming rather than just product work. Tracing their presence in these various spaces might yield information about their project development paths.

7) Capture and Visualize Collaboration: Teachers believe that collaboration is an important process for learning and an effective way to expand and reinforce one’s knowledge. They try to develop a positive attitude in students towards cooperation with others by organising teamwork activities. Collaboration is assessed after continuous observation of teamwork and teachers usually keep track of it through personal observation notes that add to the overall ‘assessment’ profile of the learner at the end of the course. However, as teachers point out this assessment strategy is highly subjective and difficult to track and thus, it remains challenging to capture collaborative skills effectively.

Then these findings were mapped to the design features of our visualisations as presented in figure 1 below.

![Figure 1](image1.png)

**Figure 1. Mapping the contextual enquiry findings with design features**

**Prototyping Visualisations**

After two prototyping iterations, we developed the visualisation presented in Figure 2. It corresponds to our findings from our contextual enquiry study in practice-based learning environments.

![Figure 2](image2.png)

**Figure 2. Snapshot of visualization designed using taking into account findings of the contextual enquiry study**

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As can be seen, it includes labels for each component of the visualisation:

A. **Visualization of Physical Computing Kit Activity:** Using an Arduino-based Smart Learning Kit, we were able to visualize the hardware and software components in use and time spend using them. For example, the “BTN” represents the use of the button component by the students, making a physical computing project. They clearly use it throughout the whole working session. Yet they use the “ACR” (accelerometer) much less frequently - showing project development patterns.

B. **Figure 3. Physical computing tools’ presentation in the visualisation**

We chose to represent the physical connection of a component as a strong thin line, the software use as a rectangle, each extending for the period of time for which they were either physically or digitally connected (Figure 3). The color of the component’s visual representation depends on whether it was an input (button, sensor, etc.) or output - thus aligning with the physical elements’ own placards as well. Any connection made is represented as a triangle on the element connected and each end of the connection on that element is represented as a square at the moment of the disconnection, again placed in line with that element’s general linear representation track.

C. **Sentiment Feedback Visualisation:** We visualized the button presses from the Sentiment Feedback Buttons (designed as part of the prototype) with a lightbulb icon (positive sentiment, e.g. “eureka idea”) and a storm-cloud icon (negative sentiment, e.g. “frustrated”, “stuck”). The icons were displayed over the visualization timeline at the moment of a corresponding button press.

D. **Screenshot From the Workstation and the Computer Screen:** We implemented a snapshot ability into each of the Sentiment Buttons such that when pressed, an overview camera from the workstation is triggered to take a picture of the students’ working environment. At the same time, a button press triggers the system to take a screenshot from the computer screen. Snapshots expand upon mouse hover and swap upon click to show the other image associated with this same time.

E. **Overall Timeline with a Manipulatable Interface:** A student or teacher can choose a slice of time that is as small as one minute or expand the slice to the full length of the session. They can look at the minute of a ‘frustration’ button press and see what modules were in use. They can also zoom out and look at the data patterns over the full period of project development. This view reveals patterns of usage behaviour such as the progression in complexity.

We are at the stage of evaluating our visualisation in real world teaching environments. We are interested to find out how educators and students engage with learning visualizations of data originating from their practice-based work, in particular supporting students’ reflections, discussions, and self-regulation, as well as educators’ awareness and assessment of the learning process. Our initial feedback from teachers and students demonstrate that the visualization could support valuable processes within practice-based STEM learning and teaching. Some of the most salient are students’ collective post-reflection and debriefing of specific difficulties within a project, and the facilitation of communication on those issues in the group and with their teacher. However, we would like to evaluate the visualisation in formal and informal teaching environments using robust research criteria with bigger samples in order to be able to draw better conclusions regarding its potential use in classrooms.
Conclusions and implications
In this paper, we presented our human-centered process for generating visualisations of face-to-face, practice-based learning activities, based on a contextual inquiry study of real world settings. We believe as our colleagues (Yu & Nakamura, 2010) that technology can capture only certain aspects of student interactions during such rich learning situations as practice-based learning activities. Hence, it is challenging to present the practice-based learning process as a whole. However, our visualisation reflects some aspects of the learning process that are considered as important by teachers and, as our initial feedback sessions demonstrate, this approach can be valuable for providing support to both teachers and students. Yet, there are other elements, which we identified in our studies as relevant and encourage future investigations, such as capturing and visualization of more heterogenous types of activities (e.g. sketching), or surfacing collaboration patterns. We hope that our visualisation will generate a productive discussion at the workshop and we can get some feedback on our visualisation of practice-based learning process as well as our approach to design it.

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Abstract: The systematic use of learning technologies has become widely employed in the past years, diverse technologies have been applied in a variety of teaching practices; for instance learning tools which allow you to flip the classroom or monitor and enhance other learning practices. However, the developed systems are only a subset of different kinds of learning materials and learning tools that an educator should take into consideration; and most importantly they do not offer an overview of the different learning experiences and dynamics. Information gathered from multiple technologies via learning analytics can allow us to orchestrate the respective technologies and practices, and support better learning. Therefore, there is an emerging need for the learning technology community to develop new knowledge about how analytics allow us to better orchestrate different e-learning tools and learning practices. In this paper, we present indicative examples of how learning analytics from different sources can allow us to make sense of learning phenomena. Our aim is to provide insights of how heterogeneous learning analytics can help us to better understand and further develop teaching approaches enhancing students’ dynamics and needs in a ubiquitous learning era.

Keywords: heterogeneous learning analytics, learning ecosystems, learning orchestration, ubiquitous learning.

Introduction

Many scholars have used "orchestration" to refer to the design and real-time management of multiple classroom activities, various learning processes and numerous teaching actions (Dillenbourg & Jermann, 2010). In 21st century’s learning spaces, instructors have to orchestrate multiple tools in the best possible way. They need a fine-grained control of time and progress. To do so, they need to translate students’ interactions into a sequence of useful information (e.g., learning progress). Contemporary learning practices and scenarios integrate individual activities (e.g. self-reading), team-work (e.g. problem solving) and class-wide activities (e.g. quizzes, lectures), an important element of these integrated activities is the required monitoring and management “orchestration”. Hence, understanding students’ interactions is even more essential in today’s education.

Siemens (2003) described learning ecosystem as a mean for orchestrating a variety of learning approaches given by the varied characteristics of learning processes. Learning ecosystem is seen as an environment which is “consistent with (not antagonistic to) how learners learn.” His approach focused on the learning process dimension and takes into account different forms of learning analytics, like learners’ characteristics and interaction with the learning environment.

The field of learning analytics is broadly concerned with how the collection, analysis and application of data can be used to improve processes and outcomes related to learning (Siemens et al., 2011). Increasing motivation, autonomy, effectiveness, and efficiency of learners and teachers is an important driver for learning analytics developments (Buckingham Shum, Gašević, & Ferguson, 2012). Learning analytics allow instructors and researchers to discover important learning episodes and phenomena (e.g., moment of learning/misconception), get better understanding of learner characteristics/needs; and understand the features that make the learning material effective. There is therefore a need to leverage learning analytics capabilities to assist instructors in the orchestration of their learning practices and respective technologies.

During the last years several technologies to assist students’ learning have been developed. For instance various Learning Management Systems (LMSs), classroom response systems and other ubiquitous learning technologies have proven their ability to improve students’ learning experience. Triangulating analytics, from different sources like video learning analytics and LMSs, has proven its enormous potential on
discovering important learning episodes and phenomena as well as portraying better understanding of learners’ experience (Giannakos, Krogstie, & Aalberg, 2016). However, the highly promising potential of combining analytics from many and diverse resources to better orchestrate e-learning tools and learning remains unexplored.

Collecting and managing integrated learning analytics from different learning spaces like video lectures, wikis, mobile learning applications, quizzes, LMSs and so forth, will allow us to better understand students’ progress, experience and usage behavior. Exploring important issues like, the dynamics between different e-learning tools, students’ prioritization of e-learning tools, the association of different orchestrations with students’ learning experience and the combination of different learning practices with different set of e-learning tools, will allow us to construct novel principles and technical knowledge in order to increase benefits arising from the efficient orchestration. Thus, there is a need to leverage learning analytics capabilities to formulate a conceptual framework for assisting researchers and instructors in improving the orchestration of e-learning tools and practices as well as harmonizing heterogeneous learning analytics streams.

Background and Open Research Question

A traditional ecosystem has been described as “the complex of living organisms, their physical environment, and all their interrelationships in a particular unit of space” (Encyclopedia Britannica (2011)). By applying this simple and good working definition to learning; we can describe a learning ecosystem “as the complex of living organisms in a learning environment (e.g. students, educators, resources), and all their interrelationships in a particular unit of space (can be digital or physical)” (Giannakos, Krogstie, & Aalberg, 2016). In a learning ecosystem it is important to consider the interrelationships of the main actors (students and educators) but also the role of the learning space (both digital and physical). The learning space is by analogy the physical environment in a traditional ecosystem, includes (organisms) information and digital resources like slides, lecture recordings, blog entries and forum discussions; but also physical materials like books, notes and handicrafts, to mention few. The space is where teaching or learning is happening and where such processes and interrelationships are conducted. The interrelationships exist (Chang & Guetl, 2007; Shum & Ferguson, 2012; Sharples, 2013) between the main actors (students and educators), the main actors with the resources, and the resources themselves (e.g. recommender systems). Those interrelationships shape the quality and value of students’ learning experience; heterogeneous learning analytics have a significant role to play in the near future, since they can help us to better understand and further develop teaching approaches enhancing students’ dynamics and needs in the emerging ubiquitous learning era of the 21st century.

Triangulating learning analytics from different learning spaces will definitely allow us to better understand and improve students’ progress and experiences. In fact we contend that the most compelling effect of learning analytics lies on their integration and synthesis in order to portray students’ learning experience. The thesis of this article is that learning analytics can inform us to better orchestrate different e-learning tools and learning practises. In particular, we pose the following open research questions as a way to guide our future work:

RQ1: What kind of learning analytics can help orchestrate a learning ecosystem?

RQ2: How can different learning analytics be integrated to improve educators’ decisions?

RQ3: How do integrated learning analytics contribute to the creation of more meaningful and efficient set of technologies for learning? and how can different technologies be coupled to help students overcome the difficulties they face while keeping them engaged?

In order to cope up with the aforementioned research questions there is a need for empirically-oriented research to develop new knowledge about how analytics allow us to better orchestrate different tools and practises. Evidence based models, tools and recommendations/guidelines drawn from large scale user-oriented studies will allow us to shed light and pave the way for richest learning experiences.

The empirically-oriented research needs to be utilized in an iterative process of: design, implementation, analysis, and revision. This will allow us to address educational problems in real-world settings, with two primary goals: to develop knowledge and solutions (McKenny & Reeves, 2012). By iteratively, designing different orchestrations, implementing them and collecting/combining diverse analytics we will be able to portray students’ progress and interaction with the materials. This will allow us to understand
how different orchestrations support students’ awareness, experience, participation, and knowledge acquisition differently. Integration of the empirical results and requirements as well as refinement of a framework with practical (e.g., best practices) and technical (e.g., systems’ design guidelines) knowledge (Figure 1), will help us to produce research that contributes towards the orchestration of multiple technologies to support better learning and teaching.

Integration of the empirical results and requirements as well as refinement of a framework with practical (e.g., best practices) and technical (e.g., systems’ design guidelines) knowledge (Figure 1), will help us to produce research that contributes towards the orchestration of multiple technologies to support better learning and teaching.

**Early Reflections**

As aforementioned, in order to be able to cope with these critical research questions there is a need for repetitive large scale empirical studies. However, in order to have some initial reflections on the thesis of this article we attempted to provide some insights of how analytics from different sources can help us to better understand students’ learning. In other words, the goal of this empirical validation is to provide some analytics-based evidence regarding the importance of the proposed research questions and approach. The early results should not be seen as an evaluation of the research questions (since they are definitely not), but as reflections rising from a particular case as well as empirical evidence for further development of the research area.

The case study in an introductory computer science course, named web technology. The focus of this course is on the World Wide Web as a platform for interactive applications, content publishing and social services. By the end of the course students are expected to be able to design and develop web-pages and web-applications. Students have to deliver specific assignments, work with a self-selected group project and take written examination; these three components are also the evaluation criteria. The course materials, digital communication as well as the assignments and project-work are orchestrated from a Learning Management System (LMS). This fundamental knowledge in this course was made available beforehand using video lectures, and weekly exercises. Upon students’ completion of the video lecture, instructors were able to access all the video analytics and visualize students’ watching behavior. Such information allowed us to make sense of students’ engagement with the video lectures.

In order to recall students’ knowledge we used a gamified classroom response system at the beginning of the class. The instructor prepared a session with questions related to the basic knowledge, supported with different forms of audio visual materials (e.g., videos). The class was equipped with a projector, which was used to project the main screen of the quiz/game, and each student used his/her own mobile phone to give the answer to the respective question (typical setup of clickers). At the end of the each class, the instructor could download all the collected analytics of the quiz/game (e.g., correct answers, response time) and explore students’ understanding.

With the visualization of the students’ watching engagement (based on repeated views, skips etc.) and score on the gamified classroom response system, we reach the conclusion that the scores are highly associated with the video engagement. As we can see from Figure 2, the highly watched videos resulted high scores during the quiz. Hence, by triangulating analytics from different resources we were able to understand why students’ scored lower in these particular quizzes.
This particular example is indeed very simple, it however allows us to understand why students’ had low/high performance the learning technology A (classroom response system) by looking into the learning analytics collected from the learning technology B (video learning analytics). Hence, by integrating heterogeneous learning analytics streams from different learning spaces will definitely allow us to understand the cause of different learning phenomena as well as improve students’ experience in 21st century learning ecosystems.

**Conclusions**

Today there is a huge demand for innovative learning and professional development, with strong impact on both academia and industry. This demand is intertwined with the move towards new modes of new ubiquitous learning technologies. Contemporary learning systems and their analytics are only a subset of different kinds of learning materials and learning tools that an educator should take into consideration; and most importantly they do not offer an overview of the different learning experiences and dynamics. Information gathered from multiple technologies via learning analytics can allow us to orchestrate the respective technologies and practices, and support better learning. Therefore, there is an emerging need for the learning technology community to develop new knowledge about how analytics allow us to better orchestrate different e-learning tools and learning practices. Making sense of heterogeneous learning analytics can bring innovation by encouraging schools, universities and life-long learning initiatives to adopt new learning practices.

In this work-in-progress contribution, we explore the notion of learning ecosystem, as well as we present an indicative example of how learning analytics from different sources can allow us to make sense of
learning phenomena. Our overreaching objective is to provide insights of how heterogeneous learning analytics can help us to better understand and further develop teaching approaches enhancing students’ dynamics and needs in a ubiquitous learning era.

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Towards a distributed framework to analyze multimodal data

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Abstract: Data synchronization gathered from multiple sensors and its corresponding reliable data analysis has become a difficult challenge for scalable multimodal learning systems. To tackle this particular issue, we developed a distributed framework to decouple the capture task from the analysis task through nodes across a publish/subscription server. Moreover, to validate our distributed framework we build a multimodal learning system to give on-time feedback for presenters. Fifty-four presenters used the system. Positive perceptions about the multimodal learning system were received from presenters. Further functionality of the framework will allow an easy plug and play deployment for mobile devices and gadgets.

Keywords: learning analytics, distributed framework, data synchronization

Introduction
Multimodal learning analytics refers to the development of effective systems to collect, synchronize and analyze data from different communication modalities, to provide on-time feedback. At the bottom of such systems, data gathered from different modalities needs to be reliable in order to analyze learner’s behavior and build predictive models that support decision-making through the learning process (Blikstein, 2013).

Nowadays, with emerging technologies and lower costs of devices, a new challenge in multimodal learning analytics has arisen. Data generated by different sensors and devices become harder to manage when trying to capture as much information as possible. Research community has strived to provide fundamentals analysis of data (Scherer, Weibel, Morency, & Oviatt, 2012; Oviatt, 2013; Worsley & Blikstein, 2015); nonetheless, there is a lack of available tools that foster an effortless deployment of such multimodal systems.

In this paper we describe a distributed framework to be used at the top of multimodal systems which helps to: 1) collect and synchronize data through a distributed architecture, 2) manage connections from different devices and sensors; and 3) organize data through recording sessions. This paper is structured as follows: First, we present the related work from former research on gathering and synchronizing data. Then, we explain how the distributed framework architecture was developed. Also, an application example is presented along with an experiment. Finally some discussion about the experience is reported together with further steps related to this work.

Related Work
Research in multimodal data has gained a lot of attention in recent years, independently of the analysis and area to be explored. The central goal of such multimodal systems is to gather data from several sources and analyze data to discover patterns. While most of the work has been done in the area of multimodal data from one source, it is still difficult to find a framework that allows a simpler interconnectivity and ease of data handling and analysis. Manual interactions such as clapping or performing a gesture are common ways that researchers use to start collecting data at the same time (Leong, Chen, Feng, Lee & Mulholland, 2015). Nevertheless, data with imprecise synchronization is the result of this approach. In the literature, we found well-structured software and frameworks to gather data from multiple inputs. These systems allow controlling several inputs through components and translating them into predefined actions or output signals from basic analysis of the data stream (Camurri et al., 2000; Hoste & Signer, 2011). One concern about the mentioned systems is that all input data is processed in the same machine, lacking of scalability to add new inputs.

A framework presented by a research group of the National Institute of Standards and Technology (Diduch, Fillinger, Hamchi, Hoarau, & Stanford, 2008) strives to capture multimodal data from several sources using a decentralized NTP server and one node for each input source. This framework is similar to the one presented in this paper but our approach differs on allowing TCP/IP connections from any input source who wants to subscribe to the capture session.
Framework Architecture

Our framework architecture is based on a publish/subscribe service to synchronize data collection, processing and storage among distributed computational nodes. Data collection is performed by nodes attached to sensors (for example a webcam, microphone, kinect, etc.), depicted as capture device nodes in Figure 1. Each capture device node subscribes to start and stop recording events with the centralized server. These events are triggered by an interface to interact with the system’s user. When the event is published, the centralized server starts to synchronize all data coming from device nodes.

At the moment the user triggers a start recording event via the session station, capture device nodes start streaming their raw data to one or more processing nodes (Figure 2). Each processing node handles an input mode, e.g., video, audio, posture, etc., and each capture device node can send one or more streams to several processing nodes (for example the capture device node for the kinect sends several streams to different processing nodes).

All data processing tasks are done in parallel while the session is recording. When the user decides to finish the session, a stop recording event is published and all capture device nodes stop their data streams. Additionally, after this event, the data aggregation service waits for all mode-processing nodes to submit their reports before preparing a feedback summary that is sent to the user (Figure 2).

The purpose of this architecture is to decouple the data processing tasks from the data capture tasks. Capture devices and mode processing nodes can easily be added or removed from the multimodal system without major reconfiguration. Upon registration, each capture device is given one or more Uniform Resource Identifiers URIs of their corresponding processing nodes.

The publish/subscribe server is implemented in a central server using Node.js while all nodes use Python to receive and send events. Messages are not queued or stored and all recorded data is time-stamped locally. All server and node clocks are synchronized using the Network Time Protocol (NTP).

Application Example: Multimodal Learning System

To test the developed framework, we created a multimodal learning system (MLS) to collect and analyze multimodal data from oral presentations’ students. The aim of the MLS is to capture data from several sensors while students present their work orally and to provide on-time feedback at the end of the presentation by analyzing nonverbal skills from gathered data. Thus, we design a physical space to locate all sensors having an immersive, non-intrusive and automatic learning system.
Figure 3. Setup of the multimodal learning system.

Figure 4. Captured frame from all six cameras.

Hardware and Software
The MLS is composed of three media streams: audio, video and Kinect data. The audio is recorded using a 6-microphone array with embedded echo cancellation and background noise reduction. This device is located at the lower border of the presenter’s field of view. Video is recorded using three Raspberry Pis, each one attached with two low-cost cameras, forming a 6-camera array that covers all sensing area (figure 3 and 4). Kinect data is recorded with a Microsoft Kinect sensor (version 1). This device is located at the lower border of the presenter’s field of view, near to the audio device. As depicted in figure 1, all recording hardware is positioned to cover the multimodal sensing area (4 m² approximately).

Data Analysis
Doing oral presentations implies the use of verbal and nonverbal communication skills. The purpose of this MLS is to explore nonverbal skills through the analysis of audio, video and Kinect data streams. Therefore,
from each data stream, a set of features are extracted and analyzed to provide a feedback message after the presentation.

The audio stream is used to measure the clarity of the speech while doing an oral presentation. We calculate the speech rate and detect the filled pauses of the presenter by following the work of De Jong & Wempe (2009) and Audhkhasi, Kandhway, Deshmukh & Verma (2009), respectively.

The video stream from the six-camera array estimates the presenter’s gaze. Four of the cameras, located in front of the presenter, indicate if the presenter is looking at the virtual audience screen, while the left and right corner cameras help to point if the presenter is looking at the presentation screen. For each video input the HAAR Cascade face detection algorithm (Lienhart, Kuranov, & Pisarevsky, 2003) is calculated and then, joining all partial results, we obtained the final gaze position, which is determined by one of the two states: facing the audience or watching presentation. At the end, we label each frame with one of the two mentioned states.

Kinect data extracts body posture from skeleton data. Each skeleton frame is composed of 3D coordinates of 20 joints from the full body. For purposes of this application, only upper limbs and torso joints are relevant to calculate body posture of presenter. To determine whether a presenter is doing an specific posture, we define three common postures founded in previous work (Echeverría, Avendaño, Chiluiza, Vásquez & Ochoa, 2014). Thus, the euclidean distances and orientation are calculated from limb to limb at a frame level and, each frame is labeled with one of the three postures.

An additional feature of the presentation was determined by analyzing the presenter’s presentation file. Thus, based on a slide tutoring system tool (Echeverria, Guaman & Chiluiza, 2015), we extracted three features from each presentation: contrast, number of words and font size. In the end, the tool determined if the presentation was good or not. The presentation was analyzed per slide and globally.

Feedback
Due to the demanding time when giving on-time feedback in traditional setups, our MLS help us to provide the feedback information right after finishing the presentation. The email that is sent to the presenter shows a summary of the states gathered from each modality. Some predefined messages were inferred after selecting a set of rules that describes whether the nonverbal communication skills were good or bad (figure 5).

![Feedback message](http://200.10.150.4/evaluator/a87d47e5d140e354aa6f3082795dc5a2f2ef93059b842ce1f7265c5987560)

**Figure 5.** Feedback message received by the presenter. Audio, postures and slides were analyzed.

Thus, for audio analysis we use speech rate and number of filled pauses to determine a set of rules that describe the performance of the presenter while speaking. As for the posture analysis, we took each Kinect frame labeled as: explaining, pointing or arms down and, calculate a percentage for each posture; with this information we also determine a set of rules to describe the presenter’s performance according to the body posture. Finally, the results obtained from the slide tutoring system tool helped to create the set of rules for the slide analysis.

Experiment
Fifty-four computer science undergraduate students, 42 male and 12 female, were asked to participate in an experiment to evaluate the proposed framework and the multimodal learning system.
Prior to the presentation, they were informed to select an oral presentation they have previously prepared. The day of the presentation, each student was briefly introduced to the learning system through an explanation on the usage of the system and immediately started the presentation.

Once the oral presentation concluded, the student observed the system’s feedback and filled a questionnaire, which consists on six questions using a 10-point likert scale (1: lower value, 10: higher value) and four open-ended questions about the learning system’s overall impression and suggestions to improve it.

After recording all students, a manual verification task was carried out to delete presentations where a source was not correctly recorded. Fifty presentations with an average of 8.52 minutes were selected as the final dataset.

Results

Learners’ feedback showed positive results about the ease of use, intrusiveness, motivation and experience with non-traditional classrooms (mode: 8), whereas students’ perception about the usefulness was reported in a lesser extent (mode: 7). Nonetheless, they think that they learnt anything with the MLS (mode: 9) compared to their previous knowledge. Table 1 shows the minimum, maximum, mode and standard deviation for each likert-scale question.

Table 2: Scores obtained from likert-scale questions.

<table>
<thead>
<tr>
<th>Question</th>
<th>Min</th>
<th>Max</th>
<th>Mode</th>
<th>Stdv.</th>
</tr>
</thead>
<tbody>
<tr>
<td>On a scale from 1 to 10 with 1 being very awkward, and 10 being very natural, how would you rate your experience with the application?</td>
<td>1</td>
<td>10</td>
<td>8</td>
<td>1.84</td>
</tr>
<tr>
<td>On a scale from 1 to 10, with 1 being very motivated, and 10 being very bored, how motivated would you be to use the application again?</td>
<td>1</td>
<td>10</td>
<td>8</td>
<td>2.95</td>
</tr>
<tr>
<td>On a scale from 1 to 10, with 1 being low, and 10 being very high, how invasive were the sensors being used to collect data about you?</td>
<td>1</td>
<td>10</td>
<td>1</td>
<td>2.88</td>
</tr>
<tr>
<td>On a scale from 1 to 10, with 1 being very likely, and being very unlikely, how likely would you be to use this application in your free time?</td>
<td>1</td>
<td>10</td>
<td>7</td>
<td>2.73</td>
</tr>
<tr>
<td>On a scale of 1 to 10, with 1 being not at all, and 10 being completely, do you feel like you learned anything while interacting with the application?</td>
<td>2</td>
<td>10</td>
<td>9</td>
<td>1.98</td>
</tr>
<tr>
<td>On a scale of 1 to 10, with 1 being much worse, and 10 being much better, how does using this application compare to how you would normally learn the same content in a traditional classroom?</td>
<td>1</td>
<td>10</td>
<td>8</td>
<td>2.05</td>
</tr>
</tbody>
</table>

From open-ended questions, learners revealed that they learnt from provided feedback specific issues related to posture; slide content and contrast; and filled pauses while speaking.

It is important to note that in the verification task we realized that some of the recordings (sources) were not correctly recorded due to the location of the device according to the presenter’s location. For instance, some audio recordings were deleted because of the lower tone of voice; in this particular case, the coverage area of the microphone was overestimated.

Discussion and future work

This paper describes the architecture of a distributed framework to gather and analyze multimodal data. The framework uses a publish/subscribe paradigm to facilitate the connectivity among nodes along with sensors. This framework also helps to maintain all the data well organized and in one place through recording sessions. The analysis of data is made on each dedicated node, which helps to boost the performance of the different algorithms for feature extraction and further analysis.

Using this framework, help researchers to be more efficient to keep all data synchronized. From this experience, we reduced the synchronization time and we put more effort on the analysis of data.

In the future, we will make this framework publicly available. We are going to test this framework not only for mobile devices (e.g. camera/voice recorder from smartphone) but also for digital pens and gadgets or any kind of sensor. In addition, we want to add some functionality such as basic feature extraction algorithms depending on the media to help multimodal community focus on the analysis of data.

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Exploring the Impact of a Tabletop-Generated Group Work Feedback on Students’ Collaborative Skills

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Abstract: This study explores the impact of a tabletop-generated feedback on student’s collaborative skills over time. Twenty-one Computer Science students participated in a three-week experimentation. A two-group design was used to assess three dimensions of collaboration: contributions, communication and respect. While the experimental group was asked to solve a database design problem using a tabletop system and received human and automatic feedback afterwards, the control group was asked to use a paper-based approach for the same task and received human feedback only. Results showed no significant difference between both groups, neither in their levels of group work skills, nor in the students’ self-perception of their group work skills. Nonetheless, there was an improvement over the whole experience on the communication dimension on the experimental group. Likewise, both conditions showed a significant improvement on students’ self-perception of their group work skills. In addition, a positive moderate correlation between the automatic and human captured data can enhance teacher’s class management activities. Nonetheless, there is a lack of straightforward task; time and attention constraints prevent educators to fully acknowledge individual’s performance and needs (Zhang, Zhao, Zhou, & Nunamaker Jr., 2004). Within this context, exploring mechanisms to aid students’ self-reflect on their collaborative skills becomes a relevant goal to pursue.

Keywords: learning analytics, tabletop systems, collaborative skills, reflection, self-perception

Introduction

Software design often demands Computer Science practitioners to successfully engage in face-to-face collaboration with peers, clients and stakeholders (Dekel & Herbsleb, 2007). Aware of this professional requirement, Computer Science programs regularly promote in-class studio-based group activities (Lee, Kotonya, Whittle, & Bull, 2015). Nonetheless, engaging in collaborative work does not necessarily lead to the development of group work skills (Dillenbourg, 1999); learning to collaborate often requires self-reflection prompted by on-time feedback (O’Donnell, 2006). Obtaining such feedback, however, is not always a straightforward task; time and attention constraints prevent educators to fully acknowledge individual’s performance and needs (Zhang, Zhao, Zhou, & Nunamaker Jr., 2004). Within this context, exploring mechanisms to aid students’ self-reflect on their collaborative skills becomes a relevant goal to pursue.

Previous work on multi-touch tabletops has shown this novel technology has a strong potential to strengthen students’ group work skills by promoting communication (Buisine, Besacier, Aoussat, & Vernier, 2012), awareness of others (Falcão & Price, 2011) and equity of participation (Wallace, Scott, & MacGregor, 2013). Moreover, the ability of tabletops to seamlessly garner traces of students’ interactions opens the possibility to timely deliver the feedback students require to engage in self-reflection (Al-Qaraghuli, Zaman, Olivier, Kharrufa, & Ahmad, 2011; Clayphan, Martinez-Maldonado, & Kay, 2013; Martinez-Maldonado, Dimitriadis, Martinez-Monés, Kay, & Yacef, 2013). In spite of the promising potential of tabletop-mediated classrooms, a deep understanding of its strengths and limitations requires studies to be carried out both over longer periods of time, and within real classroom settings where students perform tasks directly related to their interests (Xambó et al., 2013). Although some research has focused on the usage of tabletops within realistic conditions (Kharrufa et al., 2013; Martinez-Maldonado, Clayphan, & Kay, 2015), most of these studies have explored how tabletop-captured data can enhance teacher’s class management activities. Nonetheless, there is a lack of explorations of the effect visualizations of tabletop-captured data can have on students’ self-reflection process.

Additionally, several initiatives in the field of learning analytics have explored the analysis of students’ collaboration data in distributed settings (Anaya, Luque, & Peinado, 2015; Charleer, Klerkx, Santos Odriozola, & Duval, 2013; Wise, Zhao, & Hausknecht, 2013). Most of this work has focused on using the analysis to: engage students in reflection about their learning process (Anaya et al., 2015), and help students and educators gain in-line awareness of group activities (Charleer et al., 2013). However, to our knowledge no research in the field of learning analytics has explored how automatically captured data can impact students’ reflections of their collaborative skills.
In this study we examined how frequent exposure to an automatic tabletop-generated feedback can impact students’ collaborative skills over time by facilitating students’ self-reflection process. More specifically, we investigated the following three aspects: the impact of frequent on-time mixed (automatic and human-based) feedback of tabletop-supported group work on students’ collaborative skills; the impact of frequent on-time mixed (automatic and human-based) feedback of tabletop-supported group work on students’ self-s of their collaborative skills; and, the level of similitude between a tabletop-generated assessment of students’ contributions to group work and a human-based assessment. In order to explore these questions, we compared the results obtained from groups using a tabletop application to design software versus groups using a paper-based approach for the same task.

Our findings show that the students that were exposed to frequent mixed feedback do not exhibit different levels of group work skills from those that received human-based feedback only. Similarly, students’ self-perception of their levels of group work skills were not different between the two conditions. Nonetheless, students’ self-perception of their levels of group work skills, improved significantly over the whole experience in both groups. Moreover, students exposed to frequent mixed feedback showed an improvement of their ability to communicate to other team members. This indicates that tabletop-generated on-time feedback has potential to enhance the development of students’ communication skills in collaborative tasks. Interestingly, a positive moderate correlation between the automatic and human assessment of students’ contributions to group work was found. This confirms opportunities to further explore tabletop-based assessment for group work activities.

This paper is structured as follows: first, a related work section is presented and the proposed multi-touch tabletop application is described. Then, the research context, experiments and corresponding results are detailed. Finally, a discussion section along with reflections about further research is proposed.

Related Work

The emerging field of learning analytics is concerned with understanding and improving learning through the measurement, collection, analysis and reporting of data about learners and their contexts (Clow, 2012). One relevant challenge of research in the area is how to capture and offer effective visualizations of meaningful traces of learning. Work addressing this challenge usually focuses on using interviews and usability questionnaires to evaluate the potential of the proposed visualization (Anaya et al., 2015; Charleer et al., 2013; Clayphan et al., 2013; Martinez-Maldonado et al., 2013). A different challenge for learning analytics is how to place these visualizations in the context of learning, so that teachers and/or students can make reflective decisions based on the analytics. Existing work on this challenge has taken two different paths: one path draws from educational theories and suggests approaches for enhancing the effectiveness of learning analytics projects (Clow, 2012; Harfield, 2014); the other path explores what learning analytics can do for participants in realistic environments over the course of time (Martinez-Maldonado et al., 2015; McNely, Gestwicki, Hill, Parli-Horne, & Johnson, 2012). This paper focuses on this latter path: it seeks to explore how having students regularly engaging with their own data and goals can impact their activities and behaviors.

Exploring students’ collaborative actions is a problem area of interest within the field of learning analytics. Previous work on collaboration analytics has mainly focused on distributed learning settings, generating automatic context-aware recommendations for students to improve their collaboration process (Anaya et al., 2015), and proposing personal dashboards and visualizations to support students’ awareness of achievements and progress (Charleer et al., 2013). In general, learning analytics of students interacting in distributed settings often ignores that students can interact face-to-face or via other media (e.g., emails) (Charleer et al., 2013; McNely et al., 2012). Although our research pursues similar goals than previous explorations on collaborative analytics of distributed interactions, we focus specifically on studying learning analytics in the context of co-located collaboration.

Previous research on tabletops indicates this technology has the potential to enhance face-to-face collaborative learning; tabletops can encourage higher-level thinking and motivate effective learning (Kharrufa, Leat, & Olivier, 2010), elicit a more productive collaboration (Schneider et al., 2012), and support equitable participation in learning situations (Wallace et al., 2013). Furthermore, tabletops’ ability to capture traces of students’ interactions creates opportunities for studying co-located learning analytics. Relevant initiatives in the area have exploited tabletop-captured data for purposes such as: understanding the impact of users’ territoriality around the tabletop (Tang, Pahud, Carpendale, & Buxton, 2010), capturing and analyzing collaborative multimodal data to distinguish the level of collaboration of student groups (Martinez-Maldonado et al., 2013), and helping educators manage their classrooms (Martinez-Maldonado et al., 2015). Little research on face-to-face learning analytics has directly identify students as target users; Clayphan et al. (2013) studied the potential of tabletop-generated feedback to engage students in reflection on their individual and group performance. However, this author’s research did not focus on understanding the impact of feedback over time. Furthermore,
very few studies have explored tabletop applications for realistic usage scenarios, with tasks that are meaningful for both students and educators (Martinez-Maldonado et al., 2015). In contrast, the present research examines the over-time impact of face-to-face learning analytics on students, and proposes a within-the-classroom approach where participants are studied while engaging in a task of their interest (software design).

System Description

The system used for this study was a projectable multi-touch tabletop system developed to support the collaborative design of normalized-logical database models (Granda, Echeverria, Chiluiza, & Wong-Villacres, 2015). Some of the hardware component include: 1) An Optitrack Motion Tracking System, 2) A Pico projector for presenting the image of the system, 3) Up to our 3D-printed pens with infrared markers at the top, 4) Tablets. The software components are: 1) A motion tracking server system, 2) A user-interface component and 3) A web application component. Fig 1 shows an overview of the implemented solution.

Students interact with the system using pens and tablets. At any time, the motion server tracking system uses the Optitrack infrared-camera to identify markers of user’s pens. Each pen has a unique configuration of 3 infrared markers. The position of the pen tip is calculated and delivered to the user-interface component via TUIO multi-touch protocol. The user interface draws traces based on touch points from the tracking server component. Additionally, this component recognizes the shape of pen traces drawn on the canvas: if a trace with the shape of a rectangle is recognized then the trace is replaced with the shape of an Entity within the database design; if a line between Entities is drawn, a Relationship replaces the trace instead. Text input is enabled by a web component system used on tablets.

Information about each student’s activity on the tabletop (creation, edition and deletion of entities and relationships) is automatically captured. After a design session, the system sends an automatic performance report to each student’s e-mail. The report describes her contribution to the task displaying the following information: the number and percentages of entity and relationship-related actions performed by the student (create, modify, delete); the number and percentages of actions performed by the rest of the group. A pie-chart representation was chosen given the exploratory nature of this study. Figure 1 presents relevant sections of a typical system report.

Methodology

Based on our review of previous work, we formulated three research questions: RQ1, do students repeatedly exposed to an automatic and human-based feedback of their group work performance exhibit a significant improvement on their collaborative skills compared to students who only received a human-based feedback? RQ2, do students repeatedly exposed to an automatic and human-based feedback of their group work performance perceive a greater change in their collaborative skills compared to students who only received a human-based feedback? RQ3, are there similarities between a tabletop-generated assessment of individuals’ contributions to group work and a human-based assessment?

This study was conducted during the summer of 2015 at an Ecuadorian public university. It involved the participation of 21 undergraduate students enrolled in a Database System course of a Computer Science (CS) program (20 male and 1 female). An adapted version of the Readiness for Interprofessional Learning Scale (RIPLS) (Parsell, Bligh, & others, 1999) that included only the items related to teamwork and collaboration was used to form homogeneous groups. As a result, seven groups of three students were formed.

For this study, a two-group design was chosen. Students were randomly assigned to groups considering the results obtained in RIPLS. Three groups were assigned to the control condition and four to the experimental condition. The experiment consisted of three sessions. Session 1 and 2 took place the same day, and session 3 a week later. In each session, groups were assigned a database design problem; while the control group performed...
the activity using paper and markers and received human-based feedback only, the experimental group used the previously described tabletop application, receiving both, human-based and automated feedback. These activities were carried out after the midterm evaluation to allow for students to practice on Database Design topics already reviewed during the first part of the term. The instructor did not interact with the students during the tasks; he only provided formative feedback on the end result of the exercise.

During each session, a trained observer assessed each student’s group work skills. This provided us with the information needed to acknowledge any changes in individual’s performance over time. In order to gauge collaboration we derived the following dimensions both from previous work on the area (Buisme et al., 2012; Meier, Spada, & Rummel, 2007) and from the university’s expectations of group work skills: contributions (student verbal and physical useful contributions to the team’s goal), communication (student verbal expressions and physical gestures used to let the team know his/her opinion to other team members) and respect (student verbal and physical demonstrations of respect towards others opinions and actions). The observers had to total the number of actions according to the dimensions. Observers’ results were later transformed to a 0 to 2 scale: 0 if the performance of the student on a dimension did not meet the expectations, 1 if the expectation was fulfilled partially and 2 if it was completely fulfilled. Even though a wider scale could better support fine-grained ratings, the 0 to 2 scale was chosen to facilitate the assessment for the observer; due to the duration of each session, more complex methods with more cognitive load could have a negative impact on the observer’s assessment ability.

Immediately after each session, students were asked to use the same dimensions to assess their peers’ group work skills as well as their own, using the 0 to 2 scale. Additionally, the tabletop system sent the automatic generated report previously described, to students in the experimental group. Within three days after each session, all students received: a summary report comparing their self-assessment with both their observer’s and group members’ assessment (Figure 2); and guided questions to prompt a reflective writing on their group work abilities. The questions attempted to encourage students in describing the activities carried out during the task, the obstacles found, their perception on the received feedback, and the actions students planned to take in order to improve their collaborative skills for the next group activity. For the final reflection, guided questions focused on prompting students to reconsider their initial self-assessments as well as on gauging students’ perception of the tabletop usefulness. Tabletop usefulness was measured from 1 to 5, being 1: no useful and 5: very useful.

![Figure 2. Information displayed in students’ report.](image)

### Results
The results were analyzed comparing the assessment data gathered between session 1 and 3 related to the three previously established group work dimensions: contributions, communication and respect. Descriptive results from student’s evaluation show that a positive effect was observed on the contribution and communication dimensions: Session 1 (Contributions and Communication: median=1, Respect: median=2). In Session 2 all dimensions reported (median=1); In Session 3 (Contributions and Communication: median=2, Respect: median=1).

Regarding RQ1: Do students repeatedly exposed to an automatic and human-based feedback of their group work performance exhibit a significant improvement on their collaborative skills compared to students who only received a human-based feedback? A Mann-Whitney U test was employed. The results showed no significant differences in all group work dimensions (Contributions U=56.0 W=101.0 p>0.05; Communication U=56.6 W=101.5 p>0.05; Respect U=29.5 W=74.5 p>0.05). Additionally, tests for intra-group differences were performed for all dimensions. A positive effect was observed in the communication dimension of the experimental group between session 1 (median=1) and session 3 (median=2) (Z=49.5, p<0.011) whereas, the Respect dimension of the control group exhibited a negative effect (Z=0.0, p<0.020) between session 1 (median=2) and session 3 (median=1).

Regarding RQ2: Do students repeatedly exposed to an automatic and human-based feedback of their group work performance perceive a greater change in their collaborative skills compared to students who only
received a human-based feedback? No significant differences were found in any of the dimension between both conditions when using Mann-Whitney U Test (Contributions U=28.5 W=73.5 p>0.05; Communication U=34.0 W=79.0 p>0.05; Respect U=34.0 W=70.0 p>0.05). Additionally, tests for intra-group differences were performed for all dimensions. A positive effect was observed in the Contributions dimension of both the experimental and control group between session 1 and session 3 (experimental group: session 1 median=1, session 3 median= 2, Z=28.0 p<0.008; control group: session 1 median=1, session 3 median= 1, Z=10.0 p<0.046).

Regarding RQ3: Are there similarities between a tabletop-generated assessment of individuals’ contributions to group work and a human-based assessment? A Kendall Tau correlation test was performed for each session. In session 1 no significant correlation was found (rτ=0.254, p= 0.368), in session two a moderate correlation was observed, though not significant (rτ=0.4, p=0.213). Finally, in session three a moderate significant correlation was found (rτ=0.613, p =0.030). As it can be seen, an increasing trend in the correlations over time is observed too.

Furthermore, feedback about students’ perception of the tabletop usefulness was gathered. The results obtained were mixed (median=3), meaning that the solution was perceived as “useful”. Moreover, qualitative feedback was also collected. Some comments about the solution were positive, for example: “The solution seems interesting to me because, this uses a new way to interact with technology.”. Whereas some students reported: “I do not see why using this technology.”

Discussion and Further Work
This study examined the potential of over-time exposure to automatic tabletop-generated feedback on students’ collaborative skills. Results indicate that groups that received mixed feedback do not differ in their group work abilities when compared to those that received human-based feedback only. Similarly, students’ self-perception of their group work abilities was not different between the two conditions. Nonetheless, students’ self-perception of their collaborative skills, improved significantly over time on both the tabletop and the paper-based conditions. Moreover, communication skills during group work activities for the tabletop condition showed an improvement over time. These results are in line with the findings of Buisine et al. (2012), who underlined that tabletop led to more communicative gestures and more distributed verbal contributions than a paper-based approach.

Additionally, the results showed that, over time, students who did not receive any exposure to the tabletop feedback decreased their level of respect to their peers. Previous studies have concluded that pen-based interactions on a tabletop enhance group members’ awareness of others (Jamil, O’Hara, Perry, Karnik, & Subramanian, 2011); and that the presence of colored indicators to distinguish ownership of creation in tabletop systems triggers social comparison and awareness (Buisine et al., 2012). Overall, social awareness could promote respectful interactions amongst group members; the lack of features that enhance awareness of others could explain the decrease in the respect dimension of the paper-based group. Furthermore, receiving continuous tabletop-generated feedback comparing individual’s group work performance to the rest of the groups can augment individuals’ awareness of their peers. Therefore, another possible reason for students in the paper-based condition to decrease their levels of respect is the lack of tabletop-generated feedback. It is also important to note that this research’s results pertaining the level of similarity between an automatic assessment of individuals’ contributions to group work and a human-based assessment show a positive moderate correlation between both assessments. Moreover, qualitative feedback showed that this tool is promising due to the usefulness reported by students. This confirms opportunities to further explore tabletop-based assessment for group work activities.

Nonetheless, it is relevant to consider the following confluent variables that could have affected the results of the experiment: 1) the novelty effect of using a tabletop could have changed student’s behavior during the first session in terms of mutual respect and communication; 2) usability issues hindered students' abilities to seamlessly execute the tasks they intended, causing them to experience communication breakdowns; 3) the design of the automatic feedback heavily based on pie charts could have been ineffective to encourage students' understanding of the data; 4) the possible bias of using only one observer on a group of three to four students could have had a strong impact on the assessments. Future work on this area must consider a different design for the automatic feedback, as well as recording the sessions so that at least two observers have the opportunity to evaluate the groups. Finally, it is relevant to conclude that more research is needed to find the precise effect of on-time feedback by tabletop systems on collaborative skills of students.

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computer supported collaborative learning data through visualization, 329–340.


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Web-based Interactive and Visual Data Analysis for Ubiquitous Learning Analytics

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Abstract: Interactive visual data analysis is a well-established class of methods to gather knowledge from raw and complex data. A broad variety of examples can be found in literature presenting its applicability in various ways and different scientific domains. However, fully fledged solutions for visual analysis addressing learning analytics are still rare. Therefore, this paper will discuss visual and interactive data analysis for learning analytics by presenting best practices followed by a discussion of a general architecture combining interactive visualization employing the Information Seeking Mantra in conjunction with the paradigm of coordinated multiple views. Finally, by presenting a use case for ubiquitous learning analytics its applicability will be demonstrated with the focus on temporal and spatial relation of learning data. The data is gathered from a ubiquitous learning scenario offering information for students to identify learning partners and provides information to teachers enabling the adaption of their learning material.

Keywords: interactive analysis; web-based visualization; learning analytics

Introduction
Interactive visual data analysis is a well-established class of methods to gather knowledge from raw and complex data. Information visualization approaches and tools have shown high impact in various fields of research. For instance, the use of visual data analysis enables high performance computing experts to analyze code running on NUMA architectures (Weyers et al., 2014). In neuroscience, one major challenge is the analysis and interpretation of heterogeneous data resulting from simulations as well as biological experiments. Tools such as VisNEST provide coordinated multiple views which offer various perspectives on the data. Time-varying data is presented in such a way that domain scientists are able to navigate as well as analyze it (Nowke et al., 2013). From the data perspective, various types of visualization concepts can be found in literature, e.g., bar charts or pie charts (Spence, 2001) or representation concepts for relational data such as classic tables or graphs (Battista et al., 1999).

In learning analytics, only a few works can be found which address the benefits of visualization:

![Figure 1: Left: three-layered representation of ubiquitous learning logs as generated in SCROLL. Right: Web-based visualization architecture](image-url)
presenting raw and complex data in an easy to understand and interpretable manner. In context of learning dashboards, Verbert et al. (2013) present results how visualization can be used in learning analytics. Their work concentrates on a learning analytics process model in which information visualization is used to enrich learning dashboards to support students and teachers in their daily work. A similar approach has been presented by Leony et al. (2012). They present a web-based tool called GLASS that is based on a four-layered architecture. The architecture addresses the use of classic visualization components such as bar charts and the application of filters for pre-processing data. However, both works do not focus on interactive data analysis and omit the discussion of how to create suitable visualizations for learning analytics. The work of Liddo et al. (2011) presents a successful use of visualization techniques for learning analytics by using graph visualizations to represent the course of a discussion. Nonetheless, they constrain their work on a very specific use case. For location-based and mobile learning, some works can be found such as this presented by Melero et al. (2015). They present a set of visualizations for abstract information (including location) for a specific scenario, which do not offer interactive analysis features but show a relevant set of visualizations that can be used in location-based learning.

To our knowledge there is no work on the support of ubiquitous learning analytics by using interactive visualization techniques. Hence, the main contribution of this paper consists in the presentation of an architecture for ubiquitous learning analytics which is based on well-established concepts in information visualization. The applicability of this architecture will be demonstrated by means of a use case for the visualization of ubiquitous learning logs (ULLs). ULLs are gathered from learning scenarios where students use ubiquitous devices, e.g., mobile devices to track learning progress in the wild or in the class room. Logging generates spatiotemporal data that represents what the learner has acquired at which point in time (Ogata et al., 2011). ULLs can be interpreted as a four dimensional space where the first three dimensions represent the learner, the acquired knowledge, and the location. The fourth dimension represents time at which a student created the log. Beside the creation of these logs, further aspects can be included into the analysis, such as how often the ULL has been used to recall knowledge. In general, the first three dimensions can be interpreted and visualized as a graphical structure such that these dimensions can be interpreted as three layers which are related to each other as shown in Figure 1.

The paper is structured as follows. The next section presents an analysis of ULL and their specific requirements regarding interactive data analysis tools and the role of users. This discussion is followed by the presentation of an architecture for visual ubiquitous learning analytics which facilitates the information seeking mantra and the concept of coordinated multiple views. A use case is discussed which presents the feasibility of the architecture in real world scenarios. The paper concludes with a short summary and the discussion of future work.

**VISUAL DATA ANALYSIS FOR UBQUITOUS LEARNING ANALYTICS**

Ubiquitous learning data (ULD) in general and ULLs in specific present a special challenge for interactive visual data analysis approaches and tools. First, such data is heterogeneous comprising spatial, temporal as well as learning specific data (D1). For instance, ULLs contain a unique identifier for the student, data addressing the time and place where the student acquired knowledge. Second, ULD datasets can be large due to the number of users and stored data items (D2). Last, ULD has a tendency to be incomplete or to contain corrupted data by faulty entries (D3).

Beside the data requirements, a visualization architecture (VA) has to consider the analysis tasks of the user. These tasks are therefore user centric. This paper concentrates on two user roles: the teacher and the student. A user who is a teacher has certain requirements for visual analysis such as to include the obtained information contained in the ULD in the preparation of courses, extend and change course material or specifically include the ubiquitous learning infrastructure into the course. The latter could address to use of the system during the course or in between the course as well as for the definition of the final grade for a student. The student has a slightly different requirement on visual analysis system. A student can be interested in tracking achievements, in the learning progress or finding learning partners who have the same learning goals. In addition, she could be interested in where to learn best or where to find relevant learning material in her nearby surroundings. In summary, the following requirements can be identified:

- **V1:** The VA has to offer an overview of the data as well as specific details in a certain context depending on user roles
- **V2:** The VA has to offer various perspectives on the data, which reflect different requirements on the data depending on the user role
- **V3:** The VA has to offer presentations which consider different combinations of data dimensions of the underlying dataset to address the individual needs of a user
Most ubiquitous learning systems are implemented based on web technologies. To seamlessly integrate the analysis with the ubiquitous use of such learning technologies, the VA should be also based on web technologies leading to the last requirement:

V4: The VA should be implemented using web-based technologies

ULD Visualization Architecture

To address the identified requirements, the realization of a VA has to follow two methodical paradigms which are already well-established in the visualization community: the information seeking mantra and the concept of coordinated multiple views. The information seeking mantra introduced by Shneiderman (1996) is based on interactive visualization which has been shown as successful for visual data analysis (Fuchs & Hauser, 2009). Interactive visual data analysis is understood as the analysis of data using visualizations which are customizable during runtime by the user. This customization can be defined by various types of manipulations such as the application of filters, the selection of data items in a visualization, details of this selection, or the change of the visualization technique used to display a dataset. The information seeking mantra proposes and specifies a general workflow for the visual analysis process: overview first, zoom and filter, and details on demand. Thus, as a first step, a visualization tool should present an overview of the dataset. Following this, the user should be able to explore the dataset’s representation interactively by zooming into it, e.g., selecting a subset of data items, and apply filters, e.g., restricting the datasets dimensions. An architecture realizing the information seeking mantra addresses in particular D2 as well as V1 and V3.

Roberts (2007) presents an overview on coordinated multiple views. Coordinated multiple views “is a specific exploratory visualization technique that enables users to explore their data. In fact, the overall premise for the technique is that users understand their data better if they interact with the presented information and view it through different representations” (Roberts, 2007, p. 1). This is specifically true when the interpretation task benefits from different perspectives on the data by utilizing various visualization techniques and the data is multi-dimensional or heterogeneous as it is the case with ULD. The coordinated multiple view paradigm combines different types of visualizations of the same data with a coordination mechanism of views that react to user’s interaction intents accordingly. For instance, this can be a selection of a data item in one view which is then propagated to all coupled views displaying this subset in their perspective on the data (i.e., a coordination mechanism termed brushing). Analogously, the zoom and filter step of the information seeking mantra can be coordinated between views by applying the same zooming and filtering operation to all other views. A visualization architecture implementing coordinated multiple views addresses the requirements D1, V2 as well as V3. V1 is implicitly addressed because an overview of the data can be obtained by various views showing different perspectives but in combination present the whole dataset at one glance. V4 is addressed by implementing the visualization architecture as web-based components as presented in Figure 1, right. In a web-based environment, the complete dataset must be accessible by the server. By a combination of a server for the communication with the client-side visualization and the data pre-processing, a reduction of the data size can be considered to make the communication more efficient. The server-side data preprocessing should be able to pre-compute data structures, such as graph-based representations from a table-based dataset. The client-side application should offer a coordination component that provides interfaces and communication logic for the propagation of interaction events between the views. A controller view should be provided to offer a graphical user interface for general control operations, e.g., triggering the loading of datasets and the application of client- or server-side filtering operations.

Use Case – Learning Analytics for Ubiquitous Learning Logs

The applicability of the ULD visualization architecture will be shown by means of two perspectives on an analysis use case: (a) a student tries to improve her learning workflow by analyzing her own ULLs and (b) a teacher who would like to extend her learning material and activities. The gathered data originates from the SCROLL system (Ogata et al., 2011), a system for gathering ubiquitous learning logs which collects words a student observed in their everyday surrounding and which they learned for their individual vocabulary. The current implementation consists of three major visualization designs: two force-directed-layout-based interactive graph visualizations, a circular graph visualization using edge bundling, and a Google earth-based visualization of the position the ULLs have been captured, thus showing in which spatial context students learned words (see Figure 3, left). The presented visualizations are based on D3.js, a JavaScript library capable of visualizing data in web-based applications. We used different open source extensions for D3 to build these visualizations. Figure 2 shows two graph-based visualizations which represent the relation between students according to similar learned words. The left representation shows the words as light blue circles where students are represented in dark blue. The right representations only shows the relation of one specific student (here Sophie) to other
students and omits information on words they have in common. The latter information is also presented in Figure 3 on the right. Here, all students are visible and can be interactively selected such that the relations of students are highlighted. In the following, an informal description of use cases regarding the two user roles will be discussed and the potential benefit of the ULD visualization architecture identified.

Use Case - Student's Perspective
A student (Sophie) would like to find collaborators to learn new words in order to extend her vocabulary. Her first step is to find other students which have some overlap in their already learned words. Therefore, she uses the graph view presented in Figure 2, right. In a second step, she wants to find a student who knows as many words as possible that Sophie does not know yet. As both visualizations can be assumed to be coordinated linked, the selection of a student in the right view of Figure 2 is propagated to the left graph view. Sophie is now able to see which person fits to the previously defined criteria by inspecting the number of words connected to the selected student. Following this, Sophie inspects the Google earth representation which highlights the selected student’s location she is interested in to learn with. This will inform her whether the matching student is in a reachable distance. Finally, Sophie can identify the hot spots which students are visiting to learn vocabularies. This process follows the Information Seeking Mantra as Sophie first gets an overview and then selecting certain entities she is interested in. This can be interpreted as “zooming in” into the data set. Finally, by checking the location information, details are included into Sophie’s analysis.
Use Case - Teacher’s Perspective

The teacher’s use case is in various points similar to this of the student’s but follows slightly different objectives. A teacher could be interested in the interpretation and analysis of ULLs to extend or to adapt the content and the pedagogical approach she is following in class. For instance, the teacher could define learning groups for the classes along the same analysis process as described in the student use case above. On top, the teacher can identify new vocabulary to be taught in class based on prior knowledge of students and identify words unknown to most students. By zooming in and highlighting details on demand she is able to identify well-known words and topics. Finally, she can use the circular graph visualization in Figure 3 (right) to identify which students have comparable vocabulary skills.

Conclusion and Future Work

This paper explored the application of well-established visual analysis methods into the field of Ubiquitous Learning Analytics. We proposed a web-based architecture for interactive and visual ubiquitous learning analytics following two main concepts: the information seeking mantra and coordinated multiple views. By means of a simple use case, the applicability of the architecture has been shown.

For future work, the implementation and evaluation of such a framework is planned. It is planned to realize the proposed architecture in the context of e-book based instructions in various scenarios, such as MOOCs. Furthermore, we plan to analyze further visualization approaches and techniques to offer various types of analysis workflows in the future.

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Seeing Learning Analytics Tools as Orchestration Technologies: Towards Supporting Learning Activities across Physical and Digital Spaces

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Abstract: This panel paper proposes to consider the process that learners or educators commonly follow while interacting with learning analytics tools as part of an orchestration loop. This may be particularly valuable to facilitate understanding of the key role that learning analytics may have to provide sustained support to learners and educators. The complexity of learning situations where learning occurs across varied physical spaces and multiple educational tools are involved requires a holistic and practical approach. The proposal is to build on principles of orchestration that can help link technical and theoretical aspects of learning analytics with the practitioner. The panel paper provides: 1) a brief description of the relevance of the notions of orchestration and orchestrable technologies for learning analytics; and 2) the illustration of the orchestration loop as a process followed by learners or educators when they use learning analytics tools.

Keywords: learning analytics, classroom orchestration, Cross-LAK, physical and digital spaces

Introduction

It has been emphasised that learning analytics research and practice has a holistic and human-centred perspective, primarily aimed at leverage human judgement and understanding (Siemens & Baker, 2012). Learning analytics is also focused on empowering educators and learners and thus requires to keep the human in the loop. Moreover, the learning analytics community is differentiated from other educational data science perspectives because of its particular view of learning as a whole, complex activity. This includes understanding that students’ activity and their actual learning not only occurs while they interact with single learning tools (e.g. with an intelligent tutoring system or the learning management system only), but with a variety of tools, connected or unconnected with each other, and commonly distributed across different physical spaces (Pérez-Sanagustín et al., 2012).

A promising yet underexplored perspective to understand how students and educators may interact with learning analytics tools to gain a more holistic view of activity across physical and digital spaces is the metaphor of orchestration. Orchestration takes account of the variability and complexity of classrooms (and blended learning scenarios) by considering this as a question of “usability in which the classroom is the user” (Dillenbourg et al., 2011). It also recognises the key role of educators in adapting the available pedagogic and technological resources to help students achieve their intended learning goals (Dillenbourg, et al., 2011). This perspective emphasises that technology should be practical, minimalistic, controllable and flexible to facilitate rather than hinder the learning activities (Dillenbourg, 2013). An evolved notion of this approach has been embraced by the communities of Technology Enhanced Learning and Computer-Supported Collaborative Learning (Prieto et al., 2015). One of the reasons for this is that it has shown some potential to help to link research-based results with everyday educational practice.

There has only been a small number of research outputs mentioning orchestration and learning analytics together (e.g. Martinez-Maldonado et al., 2016; Rodríguez Triana et al., 2014; Verbert et al., 2013). However, there is an implicit overlap in both perspectives, particularly because learning analytics tools commonly support educators and learners by making visible aspects of their learning in order for them to take some action as a consequence.

This panel paper is aimed at generating discussion about the relevance of the notion of orchestration technology for learning analytics; and the notion of orchestration loop as a process followed by learners or educators when they use learning analytics tools.
Orchestration Technology in Learning Analytics

Prieto et al.’s (2015) orchestration framework identifies 4 main orchestration tasks that educators commonly have to perform. These are: 1) Design and planning; 2) Regulation and management; 3) Adaptation, flexibility and intervention; and 4) Awareness and assessment. Orchestration technology may support the management of the orchestration or some part of it, in one or more of these orchestration tasks. This includes, for example, interfaces that help teachers manage the class workflow, enhance their awareness or track students’ progress, or re-design the tasks after looking at the data generated in previous activities. We can easily realise that learning analytics tools are currently mostly used to support awareness and different sorts of assessment. Thus, learning analytics tools can be considered as a special type of orchestration tool just by definition. However, Martinez-Maldonado et al. (2016) demonstrated that learning analytics tools can also be used to provide support in the other orchestration tasks (e.g. during the learning design, to regulate class scripts or to perform semi-automated interventions). Mike Sharples (2013) also introduced the notion of shared orchestration, which suggested that these tasks are not just limited to the things that educators have to do, but that can be distributed among other stakeholders to different extents. For example, in self-regulated learning scenarios, the role of the teacher may exist but students have to orchestrate their own learning. This is particularly important for learning analytics for learners (Bull et al., 2016).

By contrast, an orchestrable technology allows teachers to configure or adapt the use of the technology for different purposes, before the class and/or while the class is being conducted (Tchoumikine, 2013). This can help teachers’ target the technology to a range of pedagogical objectives rather than restricting the learning analytics tool to specific educators (or students) usage. Examples of this kind of tools include efforts to create configurable open dashboards that can be customised by educators to accomplish their particular needs – see Open Learning Analytics (Siemens et al., 2011). There is also a nascent interest in collecting data from multiple data sources and trying to make sense of the learners’ heterogeneous data at a higher level. An example of this is the CLA Toolkit (Kitto et al., 2015) which provides an infrastructure to collect gather information from learner’s activity through multiple social media tools (e.g. facebook, twitter, youtube). The challenge for an educator would be how to coordinate the pedagogical approach to teaching using multiple tools but also how to make sense of the partially collected data as part of the learner’s activity may be tracked across multiple platforms.

In short, taking an approach of orchestration for learning analytics is a dynamic perspective that has the potential to attend authentic issues considering that learning activities can occur in the classroom or in other spaces. Moreover, if multiple tools are used, there is an increase in the orchestration load too (Prieto et al., 2012). For learning analytics, this may generate additional technical and pedagogic challenges to create tools that can support educators or students in making sense of learning data coming from multiple heterogeneous learning systems.

Iterative Orchestration of Learning Analytics Tools

Verbert et al. (2013) proposed that the design of visual learning analytics tools (such as dashboards) can be built and developed following an orchestration idea of “modest computing” approach (Dillenbourg, et al., 2011). This approach tries to empower people with key tools and/or information to take their own decisions, rather than automating decisions on their behalf. With this perspective in mind, the user has a crucial role in the loop where the educational technology and the learning analytics tool sits. We can understand the notion of iteration in orchestration of learning activities through learning analytics tools from a personal informatics perspective as a starting point. This has been described by Verbert et al. (2013) as the process users follow to: have access to data (i. awareness); ask questions and assess the relevance of the data (ii. reflection); answer questions, getting new insights (iii. sensemaking); to finally induce new meaning or insights (iv. impact).

This four-stage iterative process occurs while users interact with a learning analytics tool in a given phase. This process, from an orchestration perspective, mimics the orchestration loop that includes: the teacher or the student monitors the classroom or learning situation (possibly aided by a learning analytics tool), compares its state to some intended state (assessment), and adapts the scenario accordingly (intervention). This loop highlights two key tasks in the orchestration function that can be aided by learning analytics tools: state awareness (which can be improved by learning analytics tools that make visible aspects of the learning activity that may otherwise be hard to see) and workflow manipulation (which can be improved by enhancing the decision making process of the teacher or the students to self-regulate their learning).
Implications

Learning analytics can have a key role in supporting both face-to-face and blended learning activities. The learning activity is physically and socially situated and thus is strongly shaped by the tools, space and social dynamics where it sits. However, non-online learning activities have been considerably neglected by the learning analytics efforts.

The orchestration metaphor may be relevant for generating learning analytics solutions in authentic learning settings. However, how can we start the conversation between the two very different academic communities? Moreover, how can the different actors (e.g. teachers, students, developers and designers of learning analytics tools, educators and researchers) communicate and gain common understanding of the particular needs and the mutual objectives that each has?

Orchestration may be particularly important for scenarios where learning occurs in different physical and digital spaces because of its holistic perspective towards the different tasks that educators and/or learners need to do that can shape learning (e.g. design, regulation, management, intervention, evaluation, keep awareness etc.). Then, how can the metaphor of orchestration facilitate the understanding of the complexity of learning activities that occur across multiple digital environments and physical locations? A better understanding of the commonalities and particularities of each field is most needed in order to connect technical and theoretical aspects of the learning analytics research with the real-world practitioners.

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Towards integrated learning design with across-spaces learning analytics: a flipped classroom example

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Abstract: In this paper we discuss work in progress regarding the integration of learning analytics and learning design in the frame of the Integrated Learning Design Environment (ILDE). ILDE is a community platform where teachers can design learning activities using multiple authoring tools. Authoring tools can be generic, meaning that designs authored can be deployed in multiple learning systems, or specific, when designs authored can be deployed in particular systems (e.g., mobile learning applications). These particular systems may be devoted to supporting activities in specific virtual or physical spaces. For across-spaces learning designs involving multiple systems to support activities in diverse spaces, ILDE enables the selection and articulation of multiple authoring tools in what we call “design workflows”. This paper argues that this integrated approach to learning design can also benefit an articulated, meaningful interpretation of learning analytics across-spaces. This calls for an extension of ILDE incorporating learning analytics. The proposed extension is illustrated with activities across-spaces in a flipped classroom scenario.

Keywords: learning analytics, learning design, learning flow across spaces, flipped classroom

Introduction
The learning design research field deals with supporting teachers in shaping the best possible activities for their learners to learn (Laurillard, 2012; Lockyer, Bennett, Agostinho, & Harper, 2009). The activities should provide learners with the motivation for learning and offer a set of learning tasks, supporting resources and tools (Mor, Craft, & Hernández-Leo, 2013). Contributions to learning design include representations, conceptualization templates, authoring tools, design frameworks and methodologies that support teachers in the creation, sharing and implementation of learning designs (Hernández-Leo, Moreno, Chacón, & Blat, 2014; Laurillard, 2012; Lockyer et al., 2009; Mor et al., 2013; Mor & Mogilevsky, 2013). Learning design authoring tools are often specific, meaning that they support the creation of designs deployable in particular technologies for activities in virtual or physical spaces; see, for instance, QuesTInSitu for the design of learning activities in geo-located physical places (Santos, Pérez-Sanagustín, Hernández-Leo, & Blat, 2011).

The Integrated Learning Design Environment (ILDE) is a community platform where teachers can design learning activities using multiple authoring tools (Hernández-Leo, Asensio-Pérez, Derntl, Prieto, & Chacón, 2014). The design of across-spaces learning situations typically involves the use of diverse authoring tools. Each authoring tool serves to create activities to be performed in a particular space; e.g., a location-based activity outside the classroom and activities in a learning management system (Pérez-Sanagustín et al., 2012). To support an integrated design of these situations, ILDE enables the selection and articulation of multiple authoring tools in what we call “design workflows”. In this paper, we argue that this integrated approach to learning design can also benefit an articulated, meaningful interpretation of learning analytics across-spaces. This calls for an extension of ILDE incorporating learning analytics aligned with learning design.

Alignment of learning design with learning analytics research has been mostly focused on facilitating students’ self-regulation, nurture teachers’ monitoring and eventually lead to pedagogical interventions (Rodríguez-Triana, Martínez-Monés, Asensio-Pérez, & Dimitriadis, 2015; Wise, 2014; Jovanovic et al., 2008). Moreover, there is an emerging encouraging discussion about the role that learning analytics can have to inform learning design (Lockyer, Heathcote, & Dawson, 2013; Pardo, Ellis, & Calvo, 2015). The results offered by learning analytics can provide evidence to evaluate pedagogical plans and to advise their eventual reuse and redesign. The state of the art in this area is still in its early days but there are already preliminary experiences that show the potential and challenges of applying learning analytics to support learning (re)design (Mor, Ferguson, & Wasson, 2015).
Next section describes the integrated approach for learning design supported by ILDE. The following section elaborates the ideas for extending ILDE with learning analytics with an illustrative example based on the flipped classroom.

ILDE, an integrated environment for learning design

As aforementioned, learning design tools are varied. They can be oriented to the design of learning activities compliant with particular pedagogical approaches or support diverse stages of the design process (conceptualization, authoring, implementation).

Learning design conceptualization tools support teachers in reflecting about the context in which designs will be applied, e.g., Personas, Factors and Concerns (Mor & Mogilevsky, 2013), or in sketching ideas for the design, e.g., Learning Objectives, Course Features, Course Map, (Cross, S., Galley, R., Brasher, A., Weller, 2012; Mor & Mogilevsky, 2013). Authoring is the step between the conceptualization of the learning design and its implementation with students, in virtual spaces (e.g., Virtual Learning Environments, VLEs) or in physical spaces with (partial or complete) support of digital devices (of different kind, from mobile phones to laptops). Learning design authoring tools enable the production of detailed definitions of learning designs that can be deployed in a specific learning setting. Examples of authoring tools are Web Collage (Villasclaras-Fernández, Hernández-Leo, Asensio-Pérez, & Dimitriadis, 2013), for the authoring of collaborative learning activities; QuesTInSitu, for the design of location-based activities supported by mobile devices (Santos et al., 2011); or OpenGLM (Derntl, Neumann, & Oberhuemer, 2011), as a more general authoring tool whose designs can be deployed in learning management systems (Prieto et al., 2013).

An integrative approach to articulate learning design tooling can offer a holistic view of the pedagogical intent reflected in several tools used along a learning design process. ILDE enables such integrative approach by integrating multiple existing learning design tools for conceptualization, authoring and implementation in a single environment (Hernández-Leo, Asensio-Pérez, et al., 2014) (see Figure 1). In ILDE, a holistic view of the pedagogical intent is facilitated by means of a so-called learning design “workflow”.

Teachers can select which learning design tools, out of the possible options integrated in ILDE, they will be using in the process of creating a learning design. This approach envisages a scenario where teacher-led inquiry and learning analytics results can be aligned and interpreted in the frame of the whole output resulting from learning design workflow.

![Figure 1](http://ilde.upf.edu/about) Schema with some of the tools integrated in ILDE (Hernández-Leo, Asensio-Pérez, et al., 2014) (several installations of ILDE available at http://ilde.upf.edu/about).

Across-spaces learning situations typically require the use of multiple tools to support activities in diverse spaces (e.g., mobile learning applications to support activities in the physical space, learning management systems or virtual worlds to support virtual activities). The corresponding learning design authoring tools for each activity can be articulated in an integrated way in ILDE learning design workflows. Learning analytics derived from the diverse tools used to support activities in physical and virtual spaces can be also in turn documented aggregately in this type of integrated environment. The following section illustrates this idea with an example of a learning design for flipped classroom activities.
Exploring extension with learning analytics in a flipped classroom example

The example selected to illustrate proposed approach is based on the flipped classroom methodology, as an example of an across-spaces learning situation. In particular, the learning design spans a week and consists of a preparation task that learners are asked to complete online followed by a set of face-to-face activities in plenary, tutorial and lab sessions (Pardo et al., 2015).

A possible workflow to follow in the design of flipped learning activities for a week, from conceptualization to authoring, is shown in Figure 2. This workflow suggests the use of two learning design conceptualization tools to reflect and document the context (Persona Card, Factors and Concerns), two additional conceptualization tools (Learning Objectives and Heuristic Evaluation) to sketch and document the targeted learning and design objectives, the Reauthoring tool (https://bitbucket.org/abelardopardo/reauthoring) to edit the preparation tasks to be completed online with the support of computer systems and additional authoring tools to specify the activities that will be carried out in the classroom.

![Design of a flipped learning classroom in ILDE](http://ilde.upf.edu/sydneyuni). Clicking on the design of each activity design, for each space: initial preparation (virtual / before class), plenary session (physical), etc. leads to the specific design and its analytics (see Figure 3).

A particular example of the application of the workflow to design flipped learning activities for a first-year Computer Systems course at the university level entails a set of material, social and intentional factors depending on the context that are reflected in ILDE using conceptualization tools. Concerns mostly rely on the risks around lack of participation, considering the characteristics of the context (e.g., Personas: in this scenario typically tech savvy but disengaged profile, with good technical skills but plans to complete the course with minimum effort). If students do not participate actively in the preparation activities (those scheduled before the lecture), face-to-face sessions will not be effective. Moreover, if the activities in the plenary session are reduced to the exposition of factual knowledge, students will perceive no value derived from attending the session and will resort to view the recording. These concerns lead to explicit design objectives around encouraging student engagement in the preparation activities, and then schedule face-to-face sessions properly aligned with the objectives.

The learning design conceptualization undertaken sets the basis for the learning design-decision making, to be reflected in the actual authoring of the learning tasks that will be proposed to students. The previous conceptualizations identify as critical the preparation tasks to be done online, in a virtual space. Therefore, the teacher decides that the preparation tasks will contain a set of engaging exercises that will enable students to get familiar with new terms and concepts. The set of exercises consists of interacting with online videos, reading course notes, answering self-assessed formative questions, and providing the solution to a sequence of concept test questions, all supported by a computer system. Interactive actions, beyond passive watching of videos, is considered critical to foster engagement. Learners are asked to complete the preparation
tasks virtually before coming to the actual physical classroom. For the plenary session, the teacher plans active learning tasks (short exercises, exchange ideas with neighbors, voting, conducting a discussion, etc.) Tutorial sessions are based in problem-based learning and lab sessions in practical activities that require the use of electronic equipment.

The system used to support the preparation tasks has its corresponding data collecting mechanism for each exercise. The data is processed and provided to teachers, which in turn can feed ILDE to document the impact of this particular task in the context of the whole learning design and contextual characteristics (see how this could be implemented in ILDE in Figure 3). The top left graph shows the number ratio of incorrect answers in a sequence of 12 exercises. The teacher may clearly see how question number 5 has the largest rate, aspect to be considered if a potential redesign if the task is going to be reused, for example, the following academic year. Similarly, the top right graph shows the number percentage of correct, incorrect answers, and requests to view the solutions of two multiple choice questions. This analytics of the activity in the virtual space can be used to quickly detect questions with unusually high number of incorrect responses, or high number of request to see the solution is used to detect more difficult questions. Finally, the bottom of the figure shows three histograms with the number of video events recorded for three videos (from top bar, play, pause, loaded, and finished video). This visualization can be used to estimate the level of difficulty depending on the percentage of pause events.

![Figure 3](https://via.placeholder.com/150)

**Figure 3.** Tab with learning analytics information about the impact of the initial preparation task.

Those videos with an unusually large number of pause events may suggest a larger intrinsic difficulty of the described material or, considering the contextual aspects documented in the Persona Cards, special problems with the English language used in the videos for certain types of students’ profiles. Similarly, learning analytics from activities in the physical space can also feed ILDE to also provide impact information of the tasks carried out in plenary, tutorial or lab sessions (Pardo et al., 2015). By navigating through the learning designs aggregated in a design workflow, teachers can explore - in an integrative way - the learning analytics of the completed across-spaces situation. Moreover, because conceptualization aspects are also documented in the workflow, teachers can interpret the analytics considering the characteristics of the context.

**Conclusion**

Learning analytics across spaces and tools is challenging and conveys risks related to multiple and heterogeneous data sources and contextual aspects. This paper argues that risks could be minimize if learning analytics is aligned with learning design using an integrative approach. The work in progress presented in this workshop proposes an integration driven by a learning design workflow. A learning design workflow relates the set of conceptualization (documenting context) and authoring tools (enabling implementation of activities in particular spaces) used to design the across-spaces learning situation. An illustrative example shows that it is possible to link learning design of tasks that occurs in different spaces with learning analytics that exploit data for tasks distributed across spaces. Focus is on providing insights to educators about what happened in the
across-learning situation. A number of challenges remain to make feasible the implementation of the proposed idea and further investigate its implications, including the collection of data in face-to-face classrooms or the synchronization of data collection in learning systems, or the meaningful cross-analysis of heterogeneous data for holistic visualizations.

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