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Conexus Insight: learning analytics in practice

By Leah Aursand & Stian Jonson. Conexus AS, Drammen, Norway

Conexus Insight: a tool for school and municipality leaders

We would like to present a demo and/or lead a short presentation explaining our tool for learning analysis, Conexus Insight. We have developed Insight to help school and municipality leaders gather relevant education data in one place and assist them in reflecting and interpreting this data. Over recent years, we have built Conexus Insight and held workshops in municipalities around Norway to help school personnel develop inquiry-based mindsets and find their own meaning in the data. We see this as crucial to this work—without the right mindset and willingness to engage with the data, our tool won't be as useful.

Conexus Insight presents an overview of school and municipality level aggregate data from all over the education sector, including data from student surveys, mapping tests, national tests, grades, competition rates, and more. The data in Insight is password protected so that an individual municipality or school has full control over who has access to this data. We designed Insight so that individual users can search for the data they need and contextualize it. For example, it is possible to retrieve data about a certain class, group, or programme in a given school, and it is also possible to compare data from one school with data from the municipality, county, or country. It is also possible to compare one year's results to results from previous years.

Our hope is that our tool and the *use* of the results will stimulate reflection and dialogue for both individuals and organizations. Our aim has been to design a tool that meets the needs of school leaders, and not necessarily researchers or statisticians. Therefore, we do not intend to present data in the same way that it would be presented in academic journals. Instead, our goal is to present data in ways that are accessible for school leaders so that it can be used to inspire discussion and improve current practice. Through this, data can contribute to challenging existing patterns of thought in schools.

Helping school leaders reflect on their own data

We have included a number of things in Insight to help facilitate reflection and discussion. First, we present data in Insight with colour codes to help school leaders obtain a quick overview of how their results are situated nationally. Generally, values marked in green will be a good deal above the average, values marked in yellow will be right over the average, values marked in orange will be right under the average, and values marked in red will be a good deal under the average.

We also have developed a library of ready-made reflection activities for school leaders to copy and adapt for their own purposes. These activities focus on one topic for school improvement and combine data, research, and reflective questions in a format that can be exported, printed out, and used with teachers during learning meetings. Topics range from focusing on academic results (building literacy skills, analyzing national test results, etc.), to environmental factors (reducing bullying, developing classroom leadership, building deeper learning). We have also created the ability for schools and municipalities to create and share their own reflection activities.

During our demo, we will show how Conexus Insight is designed, as well as share some strengths and challenges of our work in Norway. We are excited to discuss our work with others in the learning analytics field and to share Conexus Insight as a practical tool to help support data competence in schools.

Broad Learning Outcomes			
Intrinsic Motivation	3,97	3,95	3,9
Self-efficacy	3,82	3,81	3,65
Self-assessment	3,76	3,74	3,67
Digital Skills	3,98	3,83	3,78
Communication Skills	3,75	3,66	3,59
Decision-making Skills	4,14	4,1	4,04
Citizenship	4,01	4,01	3,92

Figure 1: A screenshot of a data dashboard in Conexus Insight

Epistemic Network Analysis – a formative evaluation tool?

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Purpose and RQ

This poster presents an exploratory trial from the University College Copenhagen, Denmark, where Epistemic Network Analysis (ENA) (Shaffer, 2017) was used to develop pedagogical visualizations of the discursive network of relevant subject terms of 16 second-semester L1 teacher students' longer written assignments on literacy analysis. Our research question is: *Can ENA be used as a tool for the professor to support the understanding of subject learning and assessment when network visuals are compared to given grades (low (E-F), middle (C-D), high (A-B))?*

Theory and method: ENA

Several learning theories describe complex thinking as understanding connections among domain elements (Chi, Feltovich & Glaser, 1981; Bransford, Brown & Cocking, 1999). Shaffer (2017) builds on these ideas characterizing learning as developing an *epistemic frame*, which is made up of the "Collections of skills, knowledge, identities, values, and epistemology that professionals use to think …" (Shaffer 2006, p. 12). Therefore, a good model of (student) thinking needs to be able to analyze the relationships among domain elements. ENA is one such tool, which analyses the structure of connections by looking at the co-occurrence of concepts (codes) within a defined stanza and creates a discourse network model hereof (Shaffer, 2017). ENA enables the comparison of networks in terms of (a) complexity in terms of the number of *types* of connections, as well as *strengths* of the individual connections; and (b) statistics summarizing the weighted structure of network connections.

The students' assignment was first traditionally assessed by their lecturer (grades A-F), and then analysed with ENA to investigate whether ENA could indicate the quality of the assignment based on visuals of the network as compared to grades. As we assume that all ideas within a paragraph are related to one another while ideas across paragraphs are not, we used the paragraph in the students' assignments as stanzas. We used two sets of eight deductive codes as our units of analysis. The first eight were *general* literary analysis terms, whereas the second eight were *specific* literary analysis terms. From the 16 students, we will in our poster present detailed results for two low (n=3), two middle (n=7) and two high (n=6) performing students as examples of the analyses.

Results

Analyses indicate that ENA can visually confirm the quality of the assignments compared to given grades, as visuals match given grades, cf. figure 1. The higher performing students (grades A-B) apply a higher number of connections between subject terms (thickness of the line) as well as an increased number of *types* of connections (more codes), as compared to middle (C-D) and low (E-F) performers:

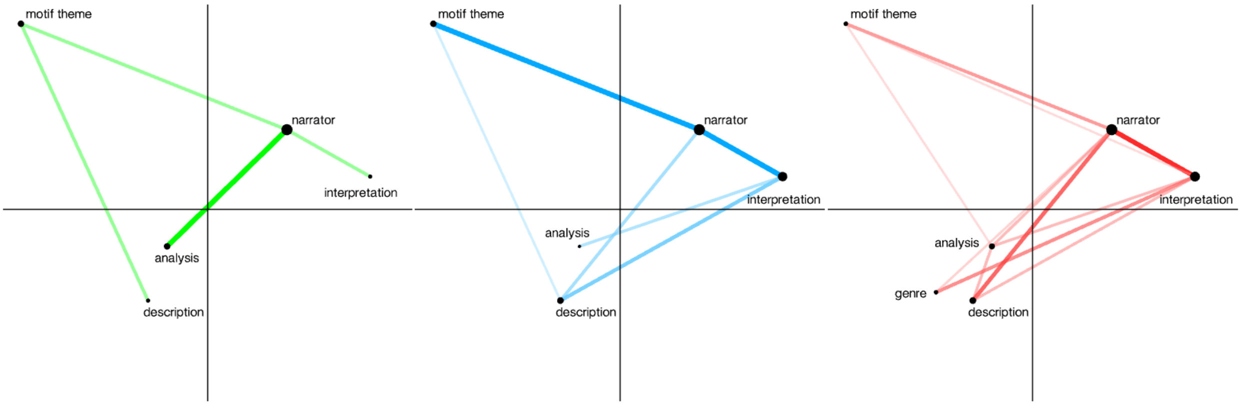

Figure 1: Examples of the epistemic network of one low performing student (green), one middle (blue) and one high student (red) in a five-page assignment on literary analysis.

Thereby ENA provides a useful tool in assessing student assignments, and our results could indicate that subject learning also could be seen as the ability to connect subject terms. One important aspect is that the ENA should not stand alone but only serve as a tool for the professor – and students.

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Some time ago, in the same galaxy not far, far away…

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ABSTRACT

Learning analytics has just taken its first steps into the world, and we already see a number of opportunities and challenges, though it is still not a part of everyday school Norway. The term "learning analytics" is not easy translated into the Norwegian language that does not distinguish between the word *analysis* and *analytics* (no:analyse). This has led to many understanding learning analytics to encompass all kinds of analysis of learning. Hence, something teachers do when assessing a text or just looking at what happens in the classroom, is regarded as "learning analytics".

In Norway it is therefore important not only to explain that learning analytics deals with "the measuring, collecting, analysing, and reporting on learners and their context, for purposes of understanding and optimizing learning and the environments in which it occurs" (Buckingham Shum & Ferguson, 2012, p.4), it is important to highlight that it is the computational approach to supporting learning and teaching based on, aggregated, analysed, and visualized data, and that learning analytics tries to provide *additional* information about learning and teaching and cannot necessary replace other approaches to promoting good learning and teaching.

In light of some years of focus on learning analytics at the Centre for the Science of Learning & Technology (SLATE), it was therefore interesting to relook at interview data from teachers dating back seven years, in these interviews teachers described their needs of technology for teaching which in many ways describes a need for learning analytics. This was before learning analytics emerged in 2010 and became a term that everybody interested in technology for learning and teaching talks about.

This poster presents some of the results of the analysis of interviews with 9 individual teachers and 3 focus groups. Findings from this study showed that teachers collected student assessment data from student groups over several years, and how they regularly use this as information for adapting their teaching. They further described how digital technology made it possibility to collect and store a lot of assessment data, while they also explain how they wished for technology that could link this data to teaching plans and the results they had given to inform on effective teaching.

Teachers also talked about how data was presented, the ability to have data visualized, and how this was dependent on available tools. Teachers explained how they used Excel and Access for

presenting the data they had collected and called for technology that could make it easier to get these data presented in different ways so that it could be used to improve teaching.

These findings report on educational needs for learning analytics and gives a retrospective view on teachers stories that explain a need for learning analytic tools, and how teachers managed to collect and analyse data with a goal of understanding and optimising their teaching, that is, for their own professional development before learning analytics was defined.

Acknowledgements

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Data Collection for Learning Analytics and OLMs

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ABSTRACT

For occupational groups, such as the Fire and Rescue Services, it is crucial to have a good overview of the competences of the workforce to be able to plan for competence maintenance *and* to close gaps where needed. In the iComPAss project one aim is to collect activity data from training and real-life incidents and use learning analytics to provide an overview of fire fighters' competences in an Open Learning Model (OLM). The OLM will be used by instructors to plan effective training, individuals to monitor their competence status, and the fire brigade leader for making decisions about development of the organisation. This poster highlights three key challenges: *What competences do the firemen need? How can we collect data from activities that inform on these competences*? *How can we visualise the competences?*

When the project started the fire, department was already using a tool (ADAPT-IT) to provide a training blueprint over the competencies that were in focus in their training, but there was no data to make an evaluation on whether the personnel had the needed competence or to inform on *what* competencies to improve or focus on further. We needed to address this issue. After interviews with the fire chief, workshops, and analysis of the fire service, first a competence map was developed in collaboration with the organisation, see figure 1, and 2) a mobile data collection app to collect assessment data about training or an incident was designed and developed. Data from training activities and incidents would then be collected through self-assessment, instructor-assessment, or team-leader assessment (in the case of incidents).

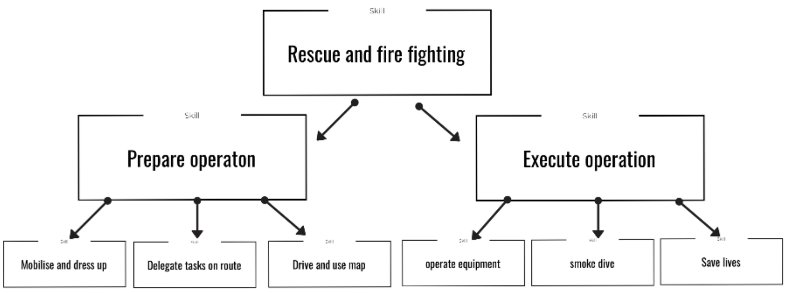

Figure 1. Part of a competence hierarchy for firefighting

The app, see figure 2, collects data on participation, type of activity, person, competence, time, and textual descriptions of the activity from the instructors and the firefighters themselves. To use the app for training the instructor plans an activity by identifying the competences to be evaluated and adding participants. Attached to each identified competence is a pre-defined performance objective, which guides the assessment of achievement level for the competence (e.g., Yes/No, a scale, a number). During the training or debriefing, the instructor and participating firefighters evaluate the performance on each competence, and in addition add textual comments if desired. The same app can be used to evaluate the performance after responding to an incident. The collected data becomes part of a larger collection of datasets about the firefighter's performances in training and incidents.

A learning analytics algorithm operates on the data and the results are visualized in an OLM. The OLM visualizes persons, teams and organization status, trends, and likely development of competences, which are used for effective planning and decision-making. Currently, the app and visualizations are been tested with the firefighters.

The biggest challenge in the project has been related to how to collect data from learning situations where the learners are engaged in activities where they are not sitting by a computer. This challenge is not unique for organisational learning situations, but also arises in the classroom, where most of the learning activity occurs in situations where digital data are collected. Such an app can be tailored for use in these situations as well.

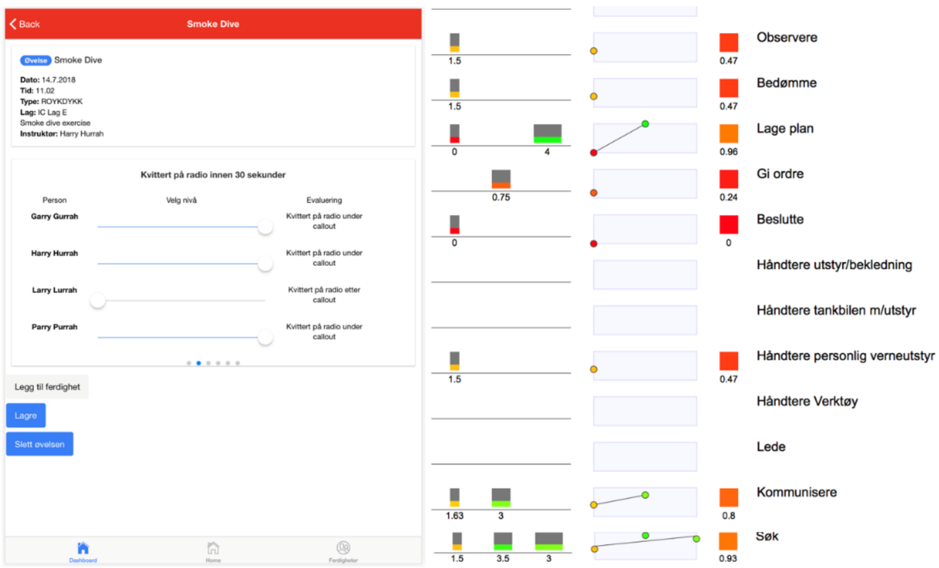

Figure 2. Data collection app and visualized data (OLM)

Acknowledgements

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How Learning Analytics supports Teachers to make good Design choices and provide timely personalized feedback to students

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ABSTRACT

Despite the early results, showing promises of learning analytics (LA) within higher education (Lockyer et al., 2013; Persico & Pozzi, 2015) evidence of its application and relevance is still fragmented. Much of the current work on LA concentrates on the supply side (i.e. development of tools, models, and frameworks) with less emphasis on the demand and pedagogical side (i.e. how analytics impact learning and teaching practices) (Ferguson et al., 2016). Questions of how LA are best deployed by instructors through innovative pedagogical processes and practices such as learning design (Goodyear & Yang, 2009) and personalized student support continue to be under-represented in empirical studies (Persico & Pozzi, 2015; Lockyer & Dawson, 2012). While the traditional summative approaches for assessment such as the end of term examinations provide feedback to teachers about students' learning, this information usually comes at the end of the marking period or semester where little support to students is possible (Picciano, 2014). Moreover, with the increasing class sizes especially in first-year courses, instructors struggle to keep track of students who are absent, disengaged, and at-risk of failure (Macfadyen & Dawson, 2012).

The aim of this doctoral study is twofold. Firstly, by building on previous research (Rienties & Toetenel, 2016) we aim to explore how teachers use analytics data as a proxy to adapt innovative pedagogical approaches such as good design choices and how this impact students' engagement/performance. Secondly, we will investigate how automated immediate feedback from analytics tools (i.e. Open Essayist) (Whitelock, Twiner, Richardson, Field, & Pulman, 2015), provide formative feedback to students before submitting an essay assignment and whether this can act as a metacognitive 'nudge' towards students' continued or improved performance, motivation, satisfaction, and self-regulation. The study will be guided by three questions:

1. How do learning analytics data & tools (i.e. Threadz) provide actionable intelligence to teachers to make good design choices?
2. To what extent are teachers' learning design decisions associated with student performance and engagement in Canvas?

3. To what extent is the automated timely learning analytics feedback (OpenEssayist) useful towards students' performance/self-regulation?

The study will take place at a large public education institution in Norway, namely the University of Oslo (UiO). The methodological framework will be Educational Design Research (EDR)(Cobb, Confrey, DiSessa, Lehrer, & Schauble, 2003) and will employ a mixed methods sequential approach. The study population will be teachers and students at the University of Oslo. In order to gather meaningful data, three user scenarios/case studies of blended courses offered in at least three different faculties will be selected. These courses will be using Canvas and any other third party or plug-in analytics tools i.e. Threadz and OpenEssayist. Data will be collected through virtual ethnography using Canvas analytics and plugged-in third-party tools. Micro level fine-grained data for individual student behaviour on the various course tasks will be collected. More data will be collected through surveys, interviews, and observation. Data analysis will be done through descriptive and inferential statistics (regression and correlation), thematic, social and interaction analysis (Jordan & Henderson, 1995).

Our hope is that this study will contribute towards an empirically based theoretical discussion about the potential affordances of learning analytics towards learning and teaching practices from the perspective of teachers and students and based on their everyday activities in a large educational institution. Moreover, by using some of the external analytics tools (e.g. Threadz, or Open Essayist) integrated with Canvas, this study might provide evidence for their formal validation and reinforce their practical relevance in teaching and learning environments. As a result, the study will produce actionable and empirical insights into the understanding of the pedagogical, contextual, technological and professional development needs, necessary for successful implementation of real-world learning analytics particularly within the Nordic region. Additionally, by employing a mixed methods approach, this study will have a methodological contribution to the learning analytics discipline, which is currently dominated by quantitative or statistical approaches. This makes the current study timely and of seminal importance in an effort to find innovative ways that can provide timely support and feedback to learners and teachers in the greater Nordics. The challenges connected to this study include the difficulties in finding appropriate plug-in learning analytics tools to integrate into Canvas and the harvesting and analysis of this data. In addition, gaining informed consent from students and getting access to relevant data about learners from the University of Oslo's LMS could be a challenge. This is because the user scenarios will be based on blended courses making it difficult to trace instructional transactions taking place during face-to-face instruction. Nonetheless, observation and field notes will minimise some of these challenges. During this Summer Institute, we intend to explore and learn more together with other learning analytics practitioners and researchers about possible ways to deal with some of these possible challenges and learn about conceptual advances.

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The Unbearable Lightness of Consent: An Eye on Learning Analytics and MOOCs

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INTRODUCTION

While many strategies for protecting personal privacy have relied on regulatory frameworks, consent and anonymizing data, such approaches are not always effective. Frameworks and Terms and Conditions often lag user behaviour and advances in technology and software; consent can be provisional and fragile; and the anonymization of data may impede personalized learning. As a part of the full study by Khalil, Prinsloo, and Slade (2018), this poster reports briefly on a dialogical multi-case study methodology of four Massive Open Online Course (MOOC) providers from different geopolitical and regulatory contexts. The main focus is on how consent is addressed and how learning analytics use student data (or personal information) in MOOCs to inform pedagogy or increase retention rates.

It can be concluded that large amounts of personal data continue to be collected for purposes seemingly unrelated to learning analytics and the delivery and support of courses. The capacity for users to withdraw or withhold consent for the collection of certain categories of data such as sensitive personal data remains severely constrained.

Methodology and Results

Two MOOCs were selected from USA (edX and Coursera) and two from Europe (iversity and FutureLearn). The geopolitical locations allowed some consideration of whether US and European legislation may have shaped approaches to 'personal data', consent and use. The units of analyses were the providers' Terms and Conditions and Privacy Policies. All contexts were copied in 8 files and prepared for text mining and analysis. Quantitative and qualitative analysis were carried out after that. Table 1 shows results from the quantitative analysis.

Table 1. Pearson correlation coefficient (*r*) of the text analysis on terms and conditions (left) and privacy policies (right) between the MOOC providers. *P-value* < 0.05

MOOC providers	***r***	**MOOC providers**	***r***
edX ↔ Coursera	0.519	edX ↔ Coursera	0.902
edX ↔ iversity	0.449	edX ↔ iversity	0.204
edX ↔ FutureLearn	0.383	edX ↔ FutureLearn	0.529

MOOC providers	***r***	**MOOC providers**	***r***
Coursera ↔ iversity	0.384	Coursera ↔ iversity	0.263
Coursera ↔ FutureLearn	0.470	Coursera ↔ FutureLearn	0.571
iversity ↔ FutureLearn	0.522	iversity ↔ FutureLearn	0.484

The quantitative analysis shows similarities between the privacy policies for the two US providers but suggests significant differences between the American and European-based MOOC providers. The European MOOC providers, on the other hand, are assumed to follow the European Data Protection Act (the prior law to GDPR).

For the direct content analysis (i.e., qualitative analysis), 'personal data', 'consent' and 'intervention' were marked, coded, and analysed. Results show that the extent to which use of data leads to personalisation or intervention is not always made clear. There is no expansion of learning analytics activities such as tracking students and whether this leads to direct intervention in cases of lack of progress, for example. What remains very much unclear are the uses to which *non-course specific* personal data might be put. None of the providers make explicit reference to this and it is perhaps of some concern that MOOC providers are gathering more information than what is needed.

All in all, it is proposed that initial consent does not provide a blank cheque to harvest and use student personal data without considering the original context of the consent. In the context of the MOOC providers studied, there is no evidence that student data is used to increase success and retention, or to offer individualized support. Despite the carried frequency analysis and the identification of words like 'privacy' in the analysed documents, it seems that consent is of little or no consequence and, indeed, is unbearably light.

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Learning Analytics from a Student Perspective: Student preferences on use of data to support academic goals and ambitions

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ABSTRACT

This poster describes the research from my Master thesis specializing in Learning Analytics, Aalborg University, spring 2018. The project presents the findings from data based on a survey conducted among first year Danish high school students (n=339) at Niels Brock Business College.

When developing and designing student dashboards to inform and guide students through their learning processes, it is necessary to ensure that the solutions are based on the actual user needs of the students. Based on interviews with students, a survey about their data preferences and academic ambitions was designed. Time was allocated for the students to simultaneously answer the online survey in class. This resulted in a considerably high response rate, 98%, and therefore the data is representative in terms of gender and academic level.

The students answered 17 different questions about their data preferences. The results reveal important information that helps our understanding of what kind of data that support students at their individual levels in terms of academic ambitions. This rich dataset tells us that students want informative data that helps them filling out their knowledge gaps and perform better. Students are less interested in comparative data like clickstream data and time spent in digital systems, which is often being used in student dashboards as an indicator of engagement.

A major finding is that the students point out a need for a data interface which let them communicate simple things back to their teacher. They want to use the interface for things like asking for extra feedback or indicating that they are struggling with specific curriculum content.

The survey also contained 14 questions concerning student ambitions and academic goals, questions about use of goal-setting, use of feedback and help-seeking behaviour. A quantitative method to calculate a score defining the level of academic ambition based on these questions is proposed. The ambition-score can ultimately be used to ensure development of data interfaces that support different student profiles in terms of their academic ambitions. It is proved that there is no correlation between this score based on data concerning academic ambitions and the grade level of the student. Thus, this gives a new perspective on analyzing student ambitions and academic goals

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Study effort and student success: a MOOC case study

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ABSTRACT

Learning was once defined as the function of efforts spent in relation to efforts needed (Carroll, 1963). Provided that effort is closely linked to time, previous research has found a positive relationship between student effort over time and student success, both in traditional university education and online education like Massive Open Online Courses (MOOCs) (Bowman, Hill, Denson & Bronkema, 2015; Wilkowski, Deutsch & Russell, 2014). However, it can be difficult to generalize findings for MOOCs that occur in different contexts (Gasevic, Dawson, Rogers & Gasevic, 2014). With the complex environment of tracing and identifying relevant data of student learning processes in MOOCs, this poster briefly summarizes our study in (Samuelson & Khalil, in press) that employed learning analytics to examine the relationship between student effort over time and student success for MITx 6.00x, an introductory programming and computer science MOOC hosted on the edX MOOC platform. A population sample from the MOOC (N = 32,621) was examined using logistic regression, controlling for variables that may also influence the outcome. Conversely, the outcome of this research study suggests that there is a curvilinear relationship between effort over time and student success, meaning those who exert effort for the longest amount of time in the MOOC actually have a lower probability of obtaining a certificate than others who exert effort over somewhat less time. One possible explanation for this finding is differences in achievement goals (Reeve, 2014, p. 255) for MOOC learners, where some may be motivated to exert effort over a long time for the sake of self-improvement, rather than proving their competence through obtaining a certificate. Future work would include examining if this type of relationship between effort over time and success will also hold for MOOCs taking place in other contexts.

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Qualitative Learner Analytics: Screen Recordings and Feedback

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INTRODUCTION AND PROBLEM

This abstract calls for an increased student and learning transfer-oriented approach in learning analytics. This abstract suggests a student-centered approach, which focuses on "how", i.e. qualitative recordings of the actions of the student. The objective of this abstract is thus to discuss a student and learning transfer-oriented model on qualitative learner analytics.

Methodology and Empirical Basis

A total of 75 students from different classes studying different programmes at Copenhagen Business School participated in five controlled studies. The five experiments resulted in 75 screen recordings, 75 case texts, 75 self-assessments and 75 rubric-based feedback sheets.

Theoretical Basis

Learning analytics is usually based on a big data approach. Conversely, this abstract is based on a thick data approach, cf. also (Lee & Sobol 2012). This abstract is based on the argument that when it comes to learning we need insights into “why” and “how” if we want to analyse and discuss how students learn and if we want to offer them performance-related feedback. Consequently, a new and more student-oriented framework was developed and tested, cf. Figure 1 below.

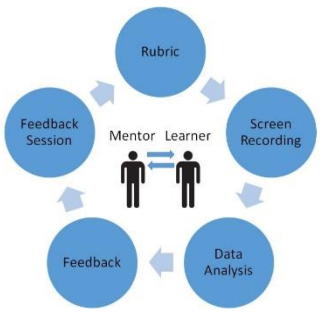

Figure 1. Model on Qualitative Learner Analytics

Discussion

Technologists have to some extent hijacked learning analytics as a field. The approach presented in this abstract attempt to get the discussion on the right track again, because it is argued that our efforts must focus on the student and the learning process. The framework shown in Figure 1 above offers an alternative approach and is called qualitative learner analytics. On the basis of the five experiments, which tested the relevance and performance of the model, it is argued that the use of screen recordings, rubrics, rubric-based feedback sheets and self-assessments are particularly powerful, because they enable the teacher and the student to focus on the "how" and the "why". It is also argued that the framework proposed also enables the teacher to design for learning, cf. also (Nortvig 2016). Finally, it is argued that learning takes place, as a social process between peers and between the student and the teacher, and this framework seems to optimally support that social learning process. Admittedly, the process is quite time-consuming, because the teacher needs to process a lot of data and spend time on personal F2F feedback sessions with the student.

Conclusion

The objectives of this abstract were to discuss a student and learning transfer-oriented model on qualitative learner analytics. On the basis of data from five controlled experiments with different classes at CBS a model on qualitative learner analytics was developed. It was found that the model works in practice, and that the students seem to appreciate and learn from the personal feedback sessions based on screen recordings and feedback rubrics. Further research in this approach is needed and experiments with automatic analysis of screen recordings and learning effect studies are planned.

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Exploring Physics Education in the Classroom and the Laboratory with Multimodal Learning Analytics

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INTRODUCTION

There is a good amount of evidence set out in recent reports that show the rising importance of working with other agents, both people and machines, to solve complex problems across subjects. The significance of collaborative problem solving (CPS) is also recognised by policy-makers and the Organisation for Economic Co-operation and Development (OECD) as a critical skill for 21st-century learning. In the case of physics education with the focus on neutron sciences in preparation for the European Spallation Source (ESS), many teaching/learning initiatives have been launched that allow for collaborative problem-solving in authentic contexts, the laboratories. Some of these initiatives are computer-based and can be used in various teaching situations ranging from blended learning to pure online courses (Udby et al., 2013). However, little is known about how the various learning tools prepare the students for actively participating in scattering experiments at the physical labs. In the case presented in this paper, we investigate how students learn in the course and how they perform in the laboratory through network analysis and multimodal learning analytics (MMLA) that capture the log-data from the digital learning activities, and interaction between students and objects from video and audio. Our research aim is to examine *how the students' actions change from the classroom to the laboratory to understand how the coursework can further support the laboratory work in real scientific experiments*.

Approach

We are investigating student behaviour in a neutron scattering science course using a combination of server logs, MMLA and observations of learners in the classroom and authentic experimental environments. We expect some students to display behaviour which can be identified as in-depth learning strategies, while other students display behaviours more associated with surface learning. However, a given student may display in-depth learning strategies at one point in time, and surface learning strategies at other points in time.

During the course, various e-learning tools (e.g. wiki-textbook, quizzes, and live-simulation of data) will be used by the students, and we will utilise the server logs of sessions to create network maps of student behaviour (Bruun et al., 2015). Concurrent with logging and analysing online behaviour, we will use video and audio recording student interactions with online course material during class and during group work that will be analysed by human and machine with ongoing MMLA work that explores group collaboration (Spikol et al., 2018; Cukurova et al., 2018). Our aim is to better understand how to design virtual simulations to prepare students to conduct experiments with complex physics instruments in the lab (Overgaard et al., 2016).

Expected Outcomes

The expected outcome of this project is to create an initial framework for combining network analysis of the students' social interactions and conceptual mappings with the physical interaction action patterns of the group work. Additionally, to explore how MMLA more data-centric approaches can be used understand the challenges the students encounter when shifting from learning about science to doing science.

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MINING FOR EUROPEAN PEDAGOGY; LOOKING INTO THE DIVERSITY OF EDUCATIONAL DESIGNS USING QUALITATIVE DATA

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INTRODUCTION AND PROBLEM

Using software for word processing affords i.e. writing. Using that tool does not require the same amount of manual dexterity nor the same eye-hand coordination as writing with a pen on paper. What else changes, when using digital tools for learning? If the digital tools in and off themselves offer affordances for some learning activities and not requiring other activities one must assume the chosen pedagogy is mirrored in the students' use of digital tools and consequently the learning outcome. Educational design needs to take both the formal and the informal teaching/learning provided by the tools into account. This poster suggests one way of mining for questions to be examined further in regard to the European Commission's "Key Competences for Lifelong Learning"

Methodology and Empirical Basis

A survey (N=375) was made in regard to the use of software for study purposes among students and teachers at two universities in Denmark. The different types of software were analysed in regard to Learning Affordances supporting the Key Competences for Lifelong Learning.

Theory

I used the European Commission's "Key Competences for Lifelong Learning" (EUR-Lex, 2006) dissolved into required learning affordances (Bower, 2008) to triangulate the qualitative data (Jansen, 2010) with Bower's affordance analysis e-learning design methodology (Bower, 2008), looking for outliers.

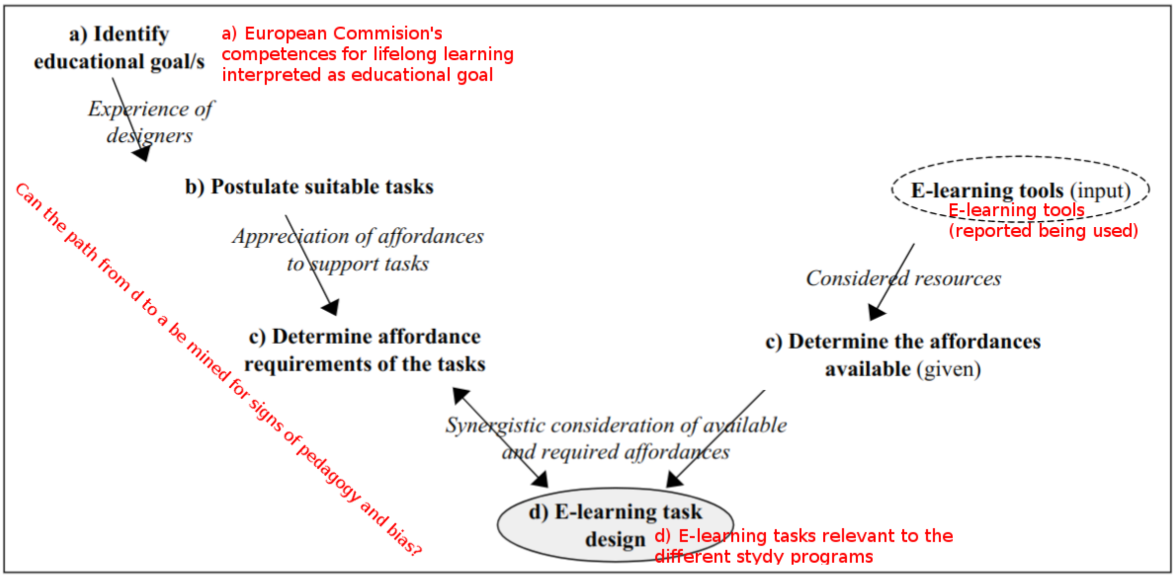

Figure 1: Affordance analysis e-learning design methodology (Bower, 2008) with my notes

Results

Here I (Soegaard, 2016) report two correlations between study program and use of digital tools with significant effect size:

- Video conference is being used more by one study program (47.4% against 27.6% on average). The study program is an online program, using video conferences as one primary way of communication between students and staff and students in study groups.

- The affordance "search-ability" did not show significance in itself, but the tools used for searching did: The use of Wikipedia was on average 25.4%, but students from one study program did not mention using it. The use of library databases was on average 10.2% and one study program reported using it significantly more with 27.8%

Analysis and Discussion

The reporting of one tool over another does not imply how the tool is being used. The use of video conference in an online master's program is an unsurprising pedagogical choice and might be indicated in the numbers. If use of search engines is tied to critical thinking, it might be worth examining the pedagogy of the study programmes further and find out if the numbers show choice or hidden bias.

Conclusion

This poster does not claim to report any results of validity. If triangulating European pedagogical goals with learning affordances at the used tools reported in the survey and qualitative statistical analysis results in a glimpse of the pedagogy and biases, the procedure could be suggestion for a stepping stone to further qualitative inquiries prior to isolating variables to be quantitatively verified.

Acknowledgement

Thank you Pantelis Papadopoulos for encouraging me to mine the data set as well as supervising me as I wrote my master thesis.

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PBL3.0: Integrating Learning Analytics and Semantics in Problem-Based Learning

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ABSTRACT

The education and training field has progressed over the years, by introducing novel learning strategies that aim to shift the focus from the educator to the learners as well as novel technologies to support learning activities (Norman & Spohrer, 1996). However, policies in the field continue to identify limitations and issues that are required to be addressed and solved (European Commission, 2010). Moreover, the current ever-changing world causes economies, trends, technologies and professional domains to constantly shift and transform. To this end, all sectors require competent employees with lifelong learning abilities and skills to quickly adapt and contribute to economic growth and boost societal benefits (EU, 2010).

This paper presents the PBL3.0 project that aims at enhancing Problem Based Learning (PBL) with Learning Analytics (LA) and Learning Semantics (LS) in order to produce a new educational paradigm and pilot it to produce relevant policy recommendations. To this end, the project constructed a new educational approach that combines a well-established learning strategy like PBL with novel technologies in learning, aiming also at respecting legal and ethical considerations (PBL_LA). Moreover, a semantic model for PBL_LA was designed that enables the annotation of learning resources in order to easily integrate them to the PBL approach and enable their discoverability when setting personalized learning pathways. During the project, a set of open source software tools, analytics tools, and an intuitive semantic annotation tool were employed in order to support the PBL_LA and the semantic model on existing Learning Management Systems (LMS). With a view to drawing evidence-based conclusions, trials employing different LMS at various sites are performed, and relevant, semantically annotated educational material is developed. Finally, the project aims at producing relevant policy recommendations for PBL_LA that could raise the quality in education and training.

In our presentation, we focus on a trial that run for one semester at Aalborg University and aimed at developing a platform employing LA for monitoring PBL semester projects. The platform is developed in Moodle, and it provides a communication and information channel between project supervisors and students, and between students belonging in the same group. Moreover, the platform

provides ways for student groups to better manage their projects, and for project supervisors to follow groups' progress. The platform is also used as a place, where students hand-in assignments that are related to their project work and report their status in the project. In this platform, we employ various LA tools offered by Moodle in order to monitor both group and individual student activity. Such tools provide learning data on individual student engagement and activity within the platform, generic statistics on the use of the platform, and insights into the exchange of information in the platform.

Acknowledgments

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Learning Analytics in Mathematics Digital Textbooks

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ABSTRACT

Teachers require information about each student's knowledge to make informed decisions, and new technologies allow for additional assistance (Stacey & Williams, 2013). As students increasingly use digital technologies, new kinds of software are developed using students as sources for data tracing of their activities on digital platforms (Suoto-Otero & Beneito-Montagut, 2016). Teachers in mathematics are beginning to use digital textbooks (DTs). They often have embedded functionalities allowing for continuous real-time measurement of students' activities including the use of learning analytics dashboards (Choppin & Borys, 2017).

However, in a study by Faber, Luyten and Visscher (2017), mathematics teachers used a digital tool in which they could follow students' progress on a dashboard to assess individuals or the whole class and assign tasks and activities. But the teachers did not use the feedback extensively. Data visualisations are not actionable if they do not disclose necessary information for teachers (Ferguson et al., 2016), and it seems to be a limited joint agreement on what information that are relevant for dashboard users in a learning context (Verbert et al., 2014). Furthermore, "there is a lack of research examining how exactly teachers respond to and make use of LA" (van Leeuwen et al., 2017, p. 43) and of the relationship between the information visualised on a dashboard related to users' reactions (Park & Jo, 2015).

To investigate how teachers made use of learning analytics embedded in DTs and how their practice was affected, we collected data from various sources. First, we selected three DTs. In those DTs, the data received through students' mathematics activities is different depending on structure and functionality of each DT. Also, the information about students visualized to the teacher is different for each DT. Three designer/developer, one from each DT, have been individually interviewed to give an understanding of ideas behind the DTs, their functionalities generally and of learning analytics dashboards specifically. Second, we have conducted interviews with nine teachers that are users of one of the DTs. The teachers were encouraged to show and explain how they use the DT with specific attention to the learning analytics dashboards and how they use the information when planning and conducting lessons. Finally, we have log data from teachers in Sweden using one of the DTs. This raw data, not yet analysed, includes students' interactions with different kinds of mathematics activities and tasks, assigned by their teachers.

Our preliminary findings show that teachers used real-time data, on group level, in the classroom to ensure that no students will be left behind. Students' data aimed for teachers to understand individual

knowledge or to address misconceptions in learning, does not appear to be of main interest. Rather, teachers wanted to use their own assessment competency. Teachers additionally said it will be a challenge if students' comprehensive mathematics understanding is supposed to be digitally assessed.

Since this is research in progress, the poster is intended to encourage discussions about research design and how to make improvements.

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Towards Detecting and Understanding Changes in Behaviour by Smart Learning Environment

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ABSTRACT

Inner layers of activities that are usually not evaluated by traditional methods, can be measured and influenced by Smart Learning Environment (SLE) (Byers, Hartnell-Young, & Imms, 2016). In order to be considered intelligent, SLE has to be effective, efficient and engaging (Spector, 2014) and with this intelligence, the gap that exists between the learning process and the environment in which it takes place can be addressed, and the adaptive space can be created (Dittoe, 2002). The analysis of behaviour of participants in the learning process can be addressed considering a number of layers that are not always clearly visible, but which could point us to potential problems and new directions of development. Problems that arise are sometimes difficult to detect on the basis of results or questionnaires, as users have a problem to define the exact cause or moment of the problem itself. Internet of things (IOT) is an area whose application in this context offers great potential (Domingo & Forner, 2010). We use it to give the learning environment a certain intelligence to understand and improve the behaviour of the participants and try to resolve the issues we have mentioned.

Changes in participants' behaviour in the learning environment depend on a large number of factors (Ramirez, McDonough, & Jin, 2017). The causes of these changes are not always clear and in order to better understand them, we have created a framework where we analyse behaviour through layers (see Figure 1). We recognize four layers, psychological, physiological, cognitive and behavioural, where for each of them we define indicators so that we can detect them through the Internet of things. Determining patterns based on the dependence between the changes occurring in the layers will help us to carry out the analysis and define the models of behaviour and communication between the participants and the smart environment. Models of behaviour and communication with a smart environment will be observed and directed through the interface design, where the basic design changes and evolves depending on the information and dependencies we want to analyse. In this way, we create a system that works on the basis of the above framework and as a result gives values that serve as input data for further analysis and intervention.

Smart learning environment is used to create a mechanism for understanding behaviours changes, with the aim of creating effective interventions that directly address problematic situations. In this way, we avoid wasting resources and focus on answering current requests and issues. Also, a smart

learning environment can introduce automation into the detection and intervention process, and in this way provides the possibility of awareness and adaptation.

In our research, we focus on a specific context - collaborative learning, and we create a new learning design where we want to examine the lowered learning environment. We introduce elements that can cause changes in the behavior of users that can be detected by systems of the smart environment, in order to examine the application of the proposed concept in a clearly defined scenario. The elements we introduce are sound (Fastl, 2006) and transitions (Joëls et al, 2006), where sound is produced by the environment and shapes transition periods as an additional element of collaborative learning design (Pijeira-Díaz et al, 2016).

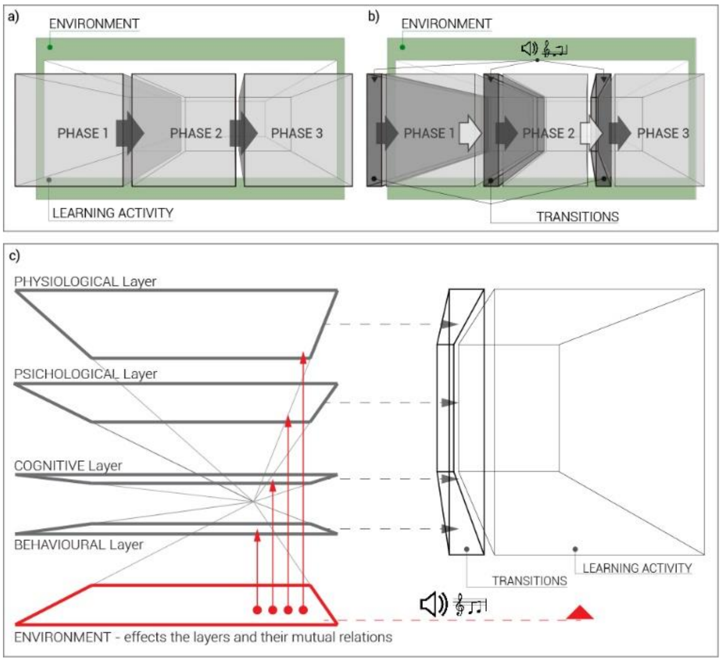

Figure 1: a) Learning activity within learning environment, b) Affecting transition phases with sound produced by environment, c) Analysis of behaviour using layers.

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Supporting firefighter training by visualising indoor positioning, motion detection, and time use: A multimodal approach

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INTRODUCTION

This poster describes the development of data driven ICT-support for firefighter training. As a study within the iComPAss project, the goal is to combine different sensor data to create visualisations of the indoor training activity of smoke diving. As a first step we have developed a system for providing a track of the firefighter's movement in a house during smoke diving training exercises.

In an overview of the field of learning analytics (LA) Misiejuk & Wasson (2017) found that there are a few examples of using LA to understand small-group learning processes. For example, Goggins et al. (2015) visualised activity analytics from student group work in order to give feedback to teachers, so they could provide support or make relevant interventions. Wolsey (2018) argues that using mobility data is an emerging trend within multi-modal analytics. For example, Martinez-Maldonado et al. (2017), who studied nurse mobility in healthcare simulations. In our research we are interested in how visualisations can facilitate post-training discussions and reflections for firefighters and training instructors.

FireTracker: Smoke Diver Data Visualisation Tool

Until recently there have been few attempts to support smoke diving with ICT. The rationale for FireTracker is that smoke diving takes place according to a set of standards and heuristics for communication, movement pattern, order of the work, etc. The standards exist to ensure firefighter safety and efficiency in an otherwise hazardous environment. By nature, these activities are carried out in partial or total blindness on the part of both the firefighters and the instructor. By creating traceability through visualisations of how these activities are carried out in practice, and making them readily available immediately after the exercise, we should be able to increase the firefighter's and instructor's ability to understand and discuss the execution of a particular exercise, and better support post-reflections on the training activity.

FireTracker, see figure 1, visualises data from smoke diving training activities based on a set of sensors. Currently, the sensors include Bluetooth Low Energy (BLE) and sensors from mobile phones such as gyroscope and GPS. The most important data are BLE. The technical infrastructure is several Bluetooth Beacons placed inside the house where the smoke diving exercise is taking place, and a mobile phone placed on the helmet or oxygen tank of the smoke diver. When the firefighters search through the building the phone collects data from the beacons and combines it with data from the (built in) gyroscope, which is used for determining if the firefighter is moving the head or body.

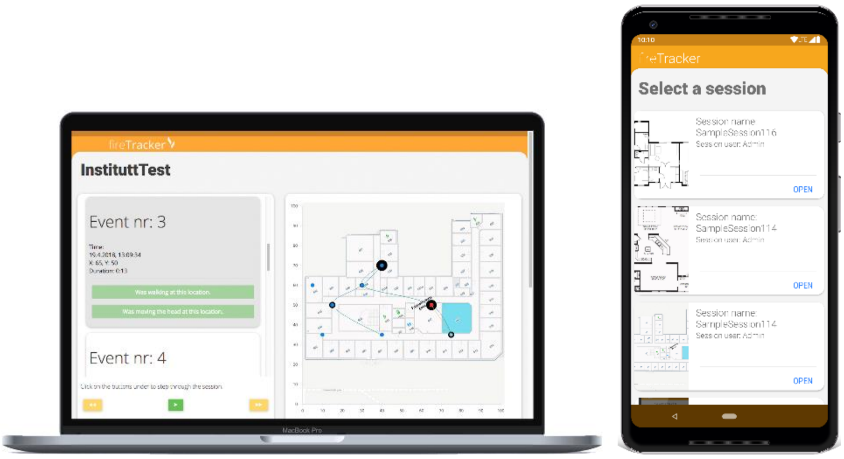

Figure 1: Screenshots of FireTracker

We also developed a web-based administration tool to enable the instructor to set up the exercise, and to have a platform for visualising the data. To set up an exercise, the training leader places a set of beacons in the building that is being used in the exercise and records their position by clicking on a corresponding map/floor plan of the building. The mobile phones placed on the firefighters are then used to record the data from the exercise. After the exercise has been completed, the data are uploaded and rendered as a track on the map of the building, that also visualises use of time and activity level at each position. The administration tool is designed to work on an iPad, to better support the physical aspect of moving around and being on your feet, which is very much a part of the exercise both for the instructors and firefighters.

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AVT: Activity data for assessment and adaptivity

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ABSTRACT

Digital learning resources and tools are increasingly used in classrooms to perform various learning- or assessment activities. These generate activity data when students watch a video, perform a task, write a text, click a link, interact with peers, and so on. It is a real challenge to gain an overview of student competence development when the activity data is spread among the different resources and tools being used in a classroom.

This poster presents the AVT (Aktivitetsdata for vurdering og tilpasning -- Activity data for assessment and adaptivity) that aims to develop a framework for sharing activity data between vendors delivering learning resources to schools in Norway (Hansen et al., 2017). The shared data is used to identify students learning gaps and make suggestions for suitable learning resources for the student.

There are three main challenges for working with activity data in Schools:

1. Vendor Silos: activity data available only to vendor owning the application where the activity was created
2. Activity data in different formats: activity data stored in the vendor's internal formats
3. National competence objectives (GREP): objectives are not fine-grained enough for designing learning activities, schools break them down (adaptivity and learning analytics)

To address these challenges, a framework of three models is being developed in collaboration with the municipality, vendors, and schools:

1. A model for appropriate structuring of learning objectives and for the structuring of content by vendors.
2. A model for sharing of data between vendors for the purpose of learning analytics

3. A model for identifying student achievement level and linking to relevant learning resources.

Model 1 addresses the organisation of learning objectives related to a school's curriculum work and the content providers' detailed themes and goals structure, and their relation to the competence objectives in the national curriculum. The Norwegian national curriculum is available in a machine-readable database (GREP). A key task is to develop a sustainable structure and management of these goals in a common database for participating vendors and suppliers.

Model 2 addresses the quality of development of vendors' coding of activity data based on the national standardisation in the field. The project has chosen xAPI, and in particular the Norwegian adaptation of xAPI. This will ensure that all vendors have equal access to activity data from the other vendors participating in the project. This includes the registration, transmission, and interpretation of these data, such as statistical validity. Figure 1 presents the architecture to support the exchange of data between vendors.

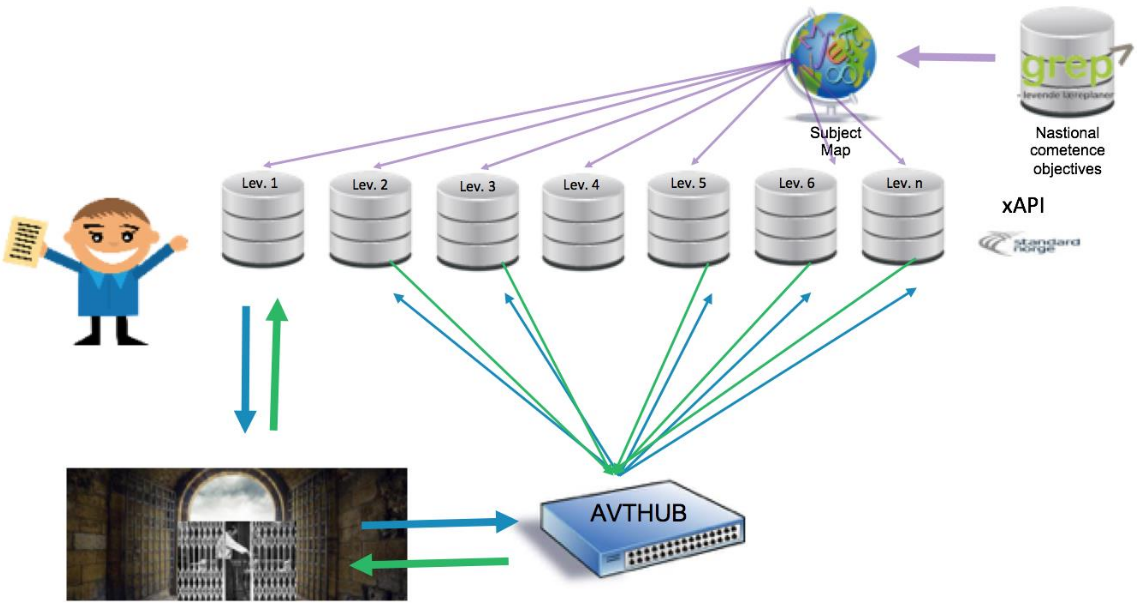

Figure 1. Architecture to support activity data exchange in Norwegian schools

Model 3 addresses the identification of student achievement level towards national competence goals, and the recommendation of relevant learning resources that addresses the student's competence gap, identified based on collected activity data.

Questions we reflect upon in the project are manifold. What kind of technological challenges do we meet? What are vendors ideas of this project? Why do they participate? What kind of standards must be used on activity data for vendors to share and use data from other vendors? How should teachers and students be presented collected data for them to make use of the resources? How can we fulfill the laws and regulations and take into account ethical issues connected to sharing of activity data? What potentials do vendors and the schools see in the use of sharing activity data?

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