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ABSTRACT: This poster describes the development and functionality of “Læringsanalyseportalen”, developed through SLATE’s Map LA project. Part of the mandate for SLATE is to carry out a national survey of the state of learning analytics in Norway, including limitations and opportunities. The Map LA (Mapping Learning Analytics) project was started to oversee this task. To carry out this task, LAP was developed. LAP is an online, dynamic mind-mapping tool, inspired by wikis, mind maps and social media for the Norwegian learning analytics community to describe itself. This poster describes the tool, including the mission, architecture and functionality.

Keywords: Online community tools, Shared mind maps, Web 2.0.

1 INTRODUCTION

The Norwegian word “dugnad” originates from the Old Norse phrase “dugnaðr”, which translates to “help, good deed, force”, and again originates from Old Norse “duge”, and means “skill, ability” and “virtue”. The concept translates to several languages, and the general meaning is voluntary work for the benefit of a community. The recently founded SLATE (Centre for the Science of Learning And Technology) at the University of Bergen has in its mandate to survey and provide an inventory of the field of learning analytics in Norway. It was decided to carry out this task within the concept of a national dugnad for the Norwegian Learning Analytics community. The Map LA project was started to oversee this task, and through this project it was decided to develop “Læringsanalyseportalen”, or “The Learning Analytics Portal” (LAP hereafter) in English, in dialogue with representatives from all the diverse organisations that constitute the Norwegian Learning Analytics community.

1.1 The Learning Analytics portal

1.1.1 LAP mission and vision

The main goal of LAP is to connect members of the diverse Norwegian Learning Analytics community with each other, and with current matters. To do this LAP visualizes the different aspects of the community, and important relations between the different aspects, as a dynamic mind map. LAP is intended to support all the different participants in the learning analytics community in Norway. The community includes public and private academic/research institutions, teaching institutions on all three levels, industry, NGOs, publishers, public service organizations, and government bodies on national, regional and local levels.
1.1.2 Architecture
LAP is constructed as a 3-layered structure, where both the data and business logic are stored as an Oracle database, and the presentation layer is managed by an Apache web server and accessed through a web browser. The end user requires only a supported web browser to use LAP. The latest version of Microsoft Edge, Mozilla Firefox, Safari, and Google Chrome are supported. The business layer is developed using Oracle Application Express (APEX). The presentation layer is developed using the d3.js (https://d3js.org/) visualisation library, in addition to selected JavaScript libraries.

1.1.3 Functionality
There are six main categories of information (Table 1), each with a set of subcategories, presented in the tree structure (Figure 1). Each category has a persistent colour, to support understanding of how kinds of information belong together when navigating the tree structure. Navigation is carried out by clicking the nodes; clicking a node for a category opens the associated subcategories. Clicking these takes the user to the nodes with associated information. Clicking on the same node again, takes the user back to the previous view. Each node displays a title for the information it contains. It is also possible to navigate the tree by using the legend presented in the centre top of the screen. Clicking end nodes containing information opens a small circle with a context-dependent summary of the information in the bottom left corner. Clicking this circle expands it, and more detailed information is presented, if available. Information can also be viewed as lists, and as selected charts. To add, delete or modify information, users have to register/log in, and use the editor mode of LAP.

![LAP tree diagram](image-url)

**Figure 1: LAP tree diagram**

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<th>Subcategory</th>
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<td>Person</td>
<td>Primary school, secondary school, tertiary education institution, private company, government organisation, publisher, research institution, network organisation</td>
</tr>
<tr>
<td>Organisation</td>
<td>Primary school, secondary school, tertiary education institution, private company, government organisation, publisher, research institution, network organisation</td>
</tr>
<tr>
<td>Educational data source</td>
<td>Statistical data, log data, assessment result, activity data, administrative data, survey data, health data, portfolio data, student survey data</td>
</tr>
<tr>
<td>Activity</td>
<td>Workshop, meeting, education, (research) project, conference</td>
</tr>
<tr>
<td>Application</td>
<td>Statistical, pedagogical, analysis service, API, student survey application, infrastructure, administration, assessment</td>
</tr>
<tr>
<td>Dissemination</td>
<td>Information, research result, government white paper, media news item, presentation, master/PhD thesis</td>
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Mapping the Field of Educational Data Sciences. Analysis of the Proceedings from Educational Data Mining, Learning Analytics and Knowledge, and Learning at Scale

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Abstract

This research takes a scientometric approach to map the complex landscape of the Educational Data Sciences field by drawing on three research communities: educational data mining, learning analytics, and learning at scale. This particular selection was motivated by the three fields being mature enough to organize their own conference: the International Conference on Educational Data Mining (EDM), the International Learning Analytics and Knowledge (LAK), and the ACM Conference on Learning at Scale (L@S).

The research dataset comprises of the all EDM, LAK, and L@S conference proceedings until 2016. In order to gain the most insights into the field four analyses with various datasets extracted from the proceedings were conducted: citation analysis to identify the sources of influence/inspiration, keyword analysis to discover the most researched topics, author analysis to determine the most important authors, and, finally, co-authorship network analysis to explore the collaboration patterns. The focus of each analysis was twofold. On the one hand, temporal analysis of each conferences development was examined, and on the other hand, the results were compared across conferences to determine their differences and similarities.

The analysis reveals that even though each conference has its own specialization, unique history, and main institutional affiliation, some formal collaboration between learning analytics, learning at scale and educational data mining communities are already established. Both citation and keywords analyses indicate not only the fields of common research interest, but also specialization areas of each conference. The author analysis suggests that there is an opportunity to increase collaboration among conferences.
Collecting video data across digital and physical spaces in a simulator environment

Charlott Sellberg

Department of Education, Communication and Learning, University of Gothenburg

The presentation reports collecting video data in a research project called “Training skills and assessing performance in simulator-based learning environments”. The project is motivated by new legislative demands in maritime education regarding training and certification in simulators. As a result, there is a need for upgraded forms of training and assessment that, on one hand, acknowledge the multifaceted nature of performance in simulator-based training, and, on the other hand, meet the criteria for certification set up by international standards. The project is a collaboration between the Department of Education, Communication and Learning at University of Gothenburg and the Department of Mechanics and Marine Sciences at Chalmers University of Technology, and draws on competences from education and maritime instructors working in the simulator environment. The aim is to investigate the use of simulator technologies in training and assessing professional performance, using a navigation course in a master mariner program as an empirical case.

The simulator-based training in the navigation course takes place in a bridge operation simulator, a simulator that combines digital projections of the marine environment with the physical space of a ship’s bridge. This involves both a bridge panel consisting of digital navigation equipment, e.g. radar technologies and electronic charts, as well as a chart table for manual plotting of positions and courses. Each training session involves ten students, working in teams of two, on five different bridges during scenarios. Meanwhile, the instructor is monitoring aspects of students’ actions by means of several computer screens in the instructor’s room. By zooming in on each bridge, the computers make available the students’ instrument settings, a shared view of the students’ look-out on the marine environment and a surveillance video of bridge team work. Moreover, a visualisation provides an overall view of the scenario from a birds-eye-perspective. Before and after each scenario in the simulator, the students gather for briefings and debriefings in a classroom adjacent to the bridge operation simulator. In the navigation course, a play-back of the scenario lays the ground for discussion and reflection on the lessons learned from the exercise.

The objective was to gather a sufficient corpus of high quality video that allows for close and detailed analyses of interactions (cf. Derry et al. 2010; Heath, Hindmarsh & Luff, 2010; Jordan & Henderson, 1995). While the different learning activities in the simulator environment is distributed across different technologies and different spaces, there were methodological challenges in finding and framing the activities. In order to meet these challenges, the data collection was designed and carried out together with project members and members of the LinCS video lab. First, at the beginning of the project in April 2013, a test filming was carried out, conducted by a senior researcher in the project. The video data captured the three different phases of a training session, briefing-scenario-debriefing, in all approximately 3 hours of video recorded data from one fixed camera. The material served as a basis for early analysis, and guided the second phase of data gathering. A pilot study was conducted during the winter of 2013 by myself with assistance from the LinCS video lab. At this time, both fixed cameras in the briefing room and in the instructor’s room were used, as well as a roving camera following the instructor moving between different spaces in the simulator environment. The data from the pilot study consist of videos from all phases of training during three different exercises, capturing in all 15 hours of training. However, the pilot study setup was not considered
successful. This was due both to the participants’ feedback that the filming interfered with their activities, as well as the difficulties of obtaining high quality video records using a roving camera. In the final setup that constitutes the main study, fixed cameras were used in the classroom to capture the briefing and debriefing phases and a fixed camera were placed in the instructors’ room to capture the instructors’ work during scenarios. In order to capture the action on the bridges, wall mounted gopro-cameras were used on each of the five bridges. At this time, during the winter 2014, three different training sessions for each exercise were recorded, in all approximately 60 hours of training.

Although using multiple cameras complicated data collection and analysis, it seemed necessary in order to be able to make sense of events that occurred during training. The fixed camera setup on each bridge was also considered less interfering for the participants than the roving camera used in the pilot study. In many ways, the data collection fulfilled the initial objectives: the empirical material has served as the basis for several studies (Sellberg, 2016; Sellberg & Lundin, 2017; Sellberg & Lundin, forthcoming) as well as a master thesis. The collaboration between the project and the LinCS lab has been an important contributor to such productive methodological work: drawing both on the instructors’ contextual knowledge as well as the LinCS lab members’ experience of collecting video data in a range of learning settings. However, there are also more lessons to be learned from the data collection. While the wall mounted gopro-cameras on each bridge offered an overview of the activities that takes place, details on radar displays and chart tables is difficult to examine. Since the instructive talk often was directed towards such representations, the trade-off between overview and detail in this project poses certain limitations on the learning analytics. One way of gaining a detailed view of the digital technologies was to retrieve data logged in the simulator system, which has been explored in collaboration with the instructors. Although the cameras were not synchronized with the logs in the simulator system, the specific details of importance can be retrieved in retrospect, albeit in a time-consuming manner. A conclusion is that it was beneficial to collect data after delimiting and specifying the research aim, thus focusing resources on capturing specific activities in the setting.

References
Learning ecologies
supported and studied through configurable technologies and analytics

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Abstract: This exploratory study advances the notion of learning ecologies, as a space for learning constructed by the students, and the question of how configurable technologies and learning can support the process and its empirical examination. Learning in our times involves being knowledgeable across a variety of contexts, with the ability to connect to remote knowledge resources, communities and sites no longer bound to one particular physical context. Research is needed to examine such processes of learning triggered by the increasingly versatile technologies that generate new opportunities and challenges at the same time. The assumption driving this envisioned empirical examination is that technologies can facilitate students in connecting with different sites of learning and access multiple resources, which enhances the construction of their learning ecologies. This contribution asserts that configurable tools and learning analytics have the potential to support the creation of an analytical framework that can contribute to this empirical endeavor.

Contemporary learning is no longer viewed as the mastering of a given subject, but involves being knowledgeable across a variety of contexts, with the ability to connect to remote knowledge resources, communities and sites no longer bound to one particular physical context (Carvalho & Goodyear, 2015). This implies that learning can emerge at the crossroads between formal education settings and other contexts (e.g., professional, personal), characterized by curricular crossovers between scholarly knowledge and professional practices and cross-boundary learning situations (Damşa & Jornet, 2016). The learners, i.e., students, educators, or professionals are placed in situations that require deliberate engagement and sustained efforts to construct own learning ecologies. Brown refers to learning ecologies as “a collection of overlapping (virtual) communities of interest, cross-pollinating with each other, constantly evolving, and largely self-organizing” (2002, p. 63).

This study takes into account the volatility of the learning situations, with students facing the challenges of the increasingly versatile technologies that generate new opportunities and challenges for learning. One main aspects of the study is represented by the examination of how configurable, hybrid environments and advanced technologies that can facilitate students constructing their learning ecologies, and can offer means to examined these processes empirically.

From an empirical perspective, it is important to advance understanding of how students create their learning ecologies, e.g., assemble and self-organize intentions, knowledge, spaces, resources, tools, activities, and/or institutional requirements, is therefore timely and of seminal importance. The assumption is that such processes are strongly influenced by affordances offered by the state-of-the-art knowledge, practices and technologies, but also by the students’ view and actions in relation to these. In this endeavor, technologies introduced either at institutional level (in courses) and those chosen by the students themselves play a critical role. Recent research has been proposing ‘orchestra’ technology (see Dillenbourg, 2013; Prieto et al., 2013), as a solution that allows configuring tailored learning environments. But in order to generate such environments there is, first and foremost, a critical need to understand what it means for the students to engage with the heterogeneous combination of technologies and the multitude of sites they are operating in. At methodological level, research aims connect to a nascent, growing interest in collecting data from multiple sources and making sense of the learners’ effort to create their learning ecologies. In this vein, in this study I aim to engage in making sense of multimodal data that documents the students’ activities taking place on multiple platforms and across contexts. Open, configurable dashboard systems (e.g., Kitto et al.,
2015), entailing web-based tools and learning analytics-based techniques (Lang, et al., 2017; Siemens et al., 2011), have potential to capture students’ interactions and distributed, cross-contextual online pursuits, and to support this methodological effort.

A first intended line investigation in this study is the empirical examination of learning ecologies as they unfold or are constructed by the students during their study period and encounters at various learning sites and how configurable technological affordances support students in constructing learning ecologies. A second line of investigation is to target a methodological contribution, i.e., understanding how technology can support the development of an integrative analytical approach for analyzing multimodal data.

Methodologies used in research in naturalistic settings-design experiments are suitable as research design. Design experiments follow an iterative strategy, with findings from initial stages feeding into the design of the follow-up studies (Sandoval, 2013). Such experiments can have an embedded substantial technological component, consisting of a set of tools to support activities in diverse spaces (e.g., mobile learning applications, virtual platforms to support online activities)—a smart environment (IASLE:http://www.iasle.net/). A likely solution is the use of a ‘primary’ virtual platform (e.g., Canvas, Bright Space), which also supports plug-in external applications students are using (e.g., Facebook, Whatsup) and has learning analytics functionalities. In relation to this, efforts are required to develop a procedure and tools for collecting and analyzing analytics data in connection to other types of data. The challenges connected to this approach involve the difficulties in harvesting analytics data from third party tools, data mashing and analysis of multimodal data. During the workshop, I intend to explore and learn more together with the other participants how such challenges could be tackled.

References
The Importance of Investigating the Macro Spaces of Learning with Multimodal Learning Analytics

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Abstract. Collaborative learning activities are a key part of education and are part of many common teaching approaches that include problem-based learning, inquiry-based learning, and project-based learning. The evidence regarding the effectiveness of open-ended collaborative small group work where learners make unique solutions to tasks that involve robotics, electronics, programming, and design artefacts is rare. Multimodal learning analytics (MMLA) can offer novel methods that can generate unique information about what happens when students are engaged in these activities. This position paper argues that although recently there is increasing interest in MMLA research, very little work has explored how the entire participant group composed of smaller student groups moves around the learning space and how different individual and group interactions are affected by the educational environment. Furthermore, the paper challenges researchers and practitioners to investigate the flow of people (students and teachers) across the different physical activities. Our hope is that this understanding can create a learning environment that intrinsically supports collaboration at a larger scale beyond small groups in the classroom.

Keywords: Multimodal Learning Analytics, Classroom activities

1 Introduction

The rapid development of technological automation has a significant impact on the future of society and the workforce. These technologies change the expectations of education. Society needs to provide learning skills for solving complex problems, working with other people, and collaborating with other agents such as machines to solve these issues. Luckin and colleagues [7] argue that these skills are set to be relevant not just to many of the jobs that will survive new waves of automation, but also our ability to cope in everyday life. Our approach in this position paper is to pose the challenge for researchers and practitioners to
expand their investigation beyond the individual (micro), the group (meso), and to consider the entire class (the macro) through the use of multimodal learning analytics (MMLA). Drawing from the PELARS project (see next section) that explored small group collaboration through the utilisation of a learning analytics system (LAS) we began to uncover the macro level of activity, however, more research and projects are needed.

2 Background

The work described in this article has been carried out as part of the Practice-based Experiential Learning Analytics Research and Support (PELARS) project, a three-year, European Union funded, research and design project\(^1\). The aim of the project was to create a system suitable for implementation in the teaching of practice-based learning activities in three learning contexts, secondary (high school) STEM subjects, third level (university) interaction design and third level engineering education. The project investigated means to understand how students learn while engaged in open-ended Collaborative Problem Solving (CPS) in PBL activities [3]. Typically, the physical design of learning interventions and the environments in which they are implemented are driven from an instrumental and technological viewpoint rather than ergonomic and human factor affordances provided to the proposed user group [6]. In order to fully support interaction and collaboration, we need to understand and consider the physical design of the collaborative workspace. As all collaboration is based on social interaction, by designing a learning environment taking into account movement and interaction on a macro (classroom) scale, we seek to encourage collaborations on a meso (group) and micro (individual) scale.

2.1 LAS

The system included customised furniture with an integrated Multimodal Learning Analytics System (LAS) capturing various data streams such as tracking of hands, faces and other objects. The Arduino platform with a visual flow bases Integrated Development Environment (IDE) logged information about the physical computing interactions. The learners and observers used mobile devices to capture multimedia data (text, images, and video) to self-document the learning activities. The automatically collected data includes the capture of objects, the positions of people, hand movements, faces and audio levels and video as well as interactions of plugged components from the Arduino-based physical computing platform and the interaction with the sentiment buttons. Instead, the mobile-based tool allows to gather self-documentation annotations from students, and progress annotations from researchers or teachers looking at students. In particular, in the experimental settings employed in this work, the researchers have annotated the activity cycle marking the phases of planning, building and reflecting.

\(^1\) http://www.pelars.eu
3 Discussion

Recent work has explored how small groups collaboratively work to solve these "wicked-like problems" see [1, 2, 4]. In other papers, we reported the results of PELARS through the lenses of the micro and "meso" though the analysis of multimodal interactions. We have through the use of machine learning and statistical regression to identify key features that include the distance of between learners, the speed of their hands, audio levels to support new ways of assessing the group's collaboration [8]. We have also explored and developed new frameworks for understanding and assessing collaborative problem solving (CPS) and applied them for the automatic coding via different approaches with supervised machine learning that used the previous features. Through the grounding of the CPS framework as the lens, the results have shown promise in helping to automate the laborious work of supporting collaboration [9]. Lastly, we have hand coded how students and teachers move throughout the entire learning space during these activities [5] to begin the investigation on the macro level. The first two approaches have provided us with relevant and promising results about how the individual and the group interact and how a LAS can be used to understand and optimise this type of learning. However, the third approach that explored how students and teachers move across space during learning activities can be seen as the missing part to give us a larger "macro" overview of how learning and teaching happens. We argue, by adding this macro view we can enable MMLA to become more applicable to the entire the learning space and its inhabitants, and this is one of the key challenges and the goals of multimodal learning analytics for the future.

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collaborative learning based on multimodal learning analytics features.
NUSILA has put the following questions to the fore.

How do Wikipedia assignments in academic settings privilege different student categories?
Collaborative discussing, writing, arguing and reviewing is powerful learning activity and can be done by creating or editing a Wikipedia article. The authenticity of the work and the experience of doing something that will be published and read by many outsiders of the classroom setting is motivating. In public scholarship, students encounter the perspectives of others (outside the school setting). The process also promotes critical thinking as students are deeply involved in discussing definitions and make (subjective) selections of how to describe a phenomenon.

Students’ willingness to share data with different stakeholders
Attitudes among Students in upper-secondary school towards sharing content and making use of data are important both for the success of a learning activity and for the personal integrity and privacy. Data generated during the teaching and learning process is often used by the teacher to improve teaching. This project focuses on the students’ use of data. Questions such as what about the awareness, and what kind of data do the students want to share, to whom, and for what purpose are investigated.

Teachers’ attitudes to make use of data from LMS
Systems used for management of learning has become ubiquitous in academic institutions. As a result, an increasing amount of data is available through learning management systems. These data contain important information of the quality and the effectiveness of education, which could be useful for monitoring and enhancing students’ performances. This may help teachers to understand and develop their course designs. But, what about the teachers’ attitude and competence to make use of it? This project will be aligned to Stockholm University’s implementation of a new learning management system 2017 – 2018.

Impact of training.
The impact of teacher training programs has always been a major concern of academic institutions. The University Rwanda focusses on the use of digital tools and materials for enhancing the quality of Higher Education. Teachers are trained on establishing e-learning approaches and use of technology in their teaching. This study is based on the user behaviour and other data of about 1000 teachers in the University of Rwanda teacher training programs and focusses on questions such as what behaviour changes result in as a result of the training, how does the learning sustained, i.e., how far do they use the knowledge from trainings in their daily teaching, how motivated the teachers are in learning new technologies.

Students’ behavior doing exams
Assessment results can help teachers improve and refine their teaching practices and help improve students’ learning and performance. Also, to understand students’ behavior doing their exams can give valuable information for the design of more reliable assessments. The project is in a planning phase.
Abstract

Smart Øving is a digital learning technology developed by Gyldendal in cooperation with Knewton.

The system seeks to keep the students in the proximal development zone by giving each student a customized task, using Knewton’s algorithm and Gyldendal’s graph of competence goals and content. If the student does not get the tasks assigned by the system administrator, the student will automatically receive content that is adapted to, and supposed to support the student.

Smart Øving is based on adaptive technology from Knewton and provides continuous updated learning analysis to the teacher. The learning analysis is based on the student’s answers and can be displayed on both an individual level and / or group level down on the individual learning objectives.

Multi Smart Øving (Math) is currently used by a wide range of schools around the country.
Title: Gaze Insights into Debugging Behavior Using Learner-Centered Analysis

Authors: Mangaroska, K., Sharma, K., Giannakos, M., Trætteberg, H., Dillenbourg, P.

Keywords: Eye-tracking, Learner-Centered Analytics, Mirroring tools, Behavior regulation, Debugging

Abstract: The present eye-tracking study investigated the correlation between a mirroring tool developed in Eclipse and users’ debugging success in a programming task. This study has five salient features (editing the code, systematic way of debugging, exercise view (EV), variable view, eye-tracking analysis) that have not been considered in the past research, creating the novelty and uniqueness of the present experiment. The aim of the study was to orchestrate a behavioral regulation of participants engaged in a debugging task. Thus, 40 computer science majors were given 40 minutes to solve 5 debugging tasks presented as a part of the main method of the main class of a 100 lines of Java code. The results have demonstrated that experts were significantly more successful than novices, and that the gaze patterns of successful debuggers corresponded with attention shifts among EV and other AOIs (i.e. console, problem, and JUnit). The fact that the time users spent on EV and their success was negatively correlated confirms that it is not important how long and how many times participants looked at the EV, but how the information they perceived from the EV guided their further actions. This fact was further examined with two and three way transitions among EV and the rest of the AOIs. The results from the analysis confirmed that the time spent in processing the information from EV and acting upon it correlates to successful completion of the debugging task.
Trajectories of Student Interaction with Learning Resources in Blended Learning. The Case of Data Science Minor

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ABSTRACT
The paper presents the preliminary results of the analysis of student learning behavior in a blended undergraduate Data Science course for a heterogenous group non-STEM students. To identify learning trajectories, a mixture model was applied to cluster students according to the use of available resources in the course. Clustering results suggest the existence of five different learning trajectories with varied resource use.

CCS CONCEPTS
•Social and professional topics → Computing education programs; •Applied computing → Computer-assisted instruction;

KEYWORDS
hybrid learning, blended learning, data science

1 INTRODUCTION
Current developments of learning analytics in online and blended courses are facilitated by the growing availability of the data on students’ learning traces in virtual learning environments (VLE). These traces include, for instance, time spent on doing the homework, engagement in coding, measurements of computer-mediated communication between students and the results of students’ self-reported assessment of their learning experience.

Another trend of modern education is the active implementation of VLEs and learning management systems (LMS), designed for personalized and adaptive learning of students [1]. However, students do not fully use the available resources for independent work in such environments to get a full understanding of the subject due to various reasons including the lack of knowledge about the available resources among students or the motivation to use it [6].

The collection of students’ trace data allows us to address the connection between the students’ trajectories of interaction with learning resources and academic achievements in a more detailed way.

Unsupervised machine learning algorithms such as clustering and sequential pattern mining were found useful for mining unobservable constructs such as learning trajectories from learning traces [5]. Studies often detect several types of educational technology users [2, 4, 6] with respect to the learning outcome.

Research on mining learning trajectories in the field of LA include studies in blended learning settings where an online component is used in addition to face-to-face classroom teaching. In the blended learning environment, the direct contact with teachers is less intensive compared to the traditional classroom settings.

Therefore, to support student engagement in the courses, and to develop educational programs that consider different student learning trajectories, it is important to study how students use educational resources in blended learning courses.

2 DATA AND METHODS
In the current work, we use data on 193 students enrolled in the minor specialization in Data Science in blank. The specialization is interdisciplinary and unites undergraduate students from different social sciences and humanities educational programs. Students learn basics of data analysis, machine learning, and computer science.

The core technologies used in the minor specialization are the server-side implementation of the RStudio – the environment for data analysis, and the Q&A forum for students’ discussions of the course-related topics.

Additional component of the specialization is the private course on the online educational platform Stepik.org. This online course provides students with additional materials and assignments with an unlimited number of attempts and time for completion. These materials complement the main topics covered in the classroom with the instructor, e.g. data aggregation or text mining, with the aim of improving knowledge acquisition through additional practice.

Seven variables were constructed to reflect interaction trajectories of students: coding activity, measured by the number of lines of code written by the student in VLE (r_logs) and how much of this activity takes place outside of the classroom (independent_study); communication on the Q&A forum was divided into two activities: posting a question or the tutorial and starting a discussion thread (forum_posts), and commenting and answering questions of others (forum_answers); activity on the online course on the Stepik platform is measured as a percentage of completed additional exercises (stepik_percentage); the percentage of wrong submission attempts on the online course (stepik_percentage_wrong); attendance on face-to-face classroom sessions shows general involvement in the course (attendance). Additionally, the sum of the students’ test scores was used to see the differences in resulted clusters in terms of the academic achievement.

To group together students who have similar patterns of the use of educational resources we used latent profile analysis technique.
Model-based clustering algorithm revealed 5 distinct groups. The group means for given variables in each cluster are shown in Table 1. Kruskal-Wallis test showed that all clusters are significant (p < .05). Further discussed only significant differences between groups at the 95% confidence level, obtained through the Dunn’s test.

In terms of the academic performance, Clusters 1, 3 and 4 have similar grades with no significant differences. The only difference is between Cluster 2 – the least active students with respect to resource use and Cluster 5 – the most active ones.

The largest group of 93 students, represents the Cluster 4 with overall below average activity. They have low usage of RStudio outside of the classroom (M = 50.2) and have the least code written (M = 3167.5). They also have low attendance (M = 10.3) and do not participate in the forum discussions, but however, they manage to maintain average grades for the course.

Cluster 1 unites students with the slightly higher resource use level compared to Cluster 4. Students have contributed to the forum via posting (M = 2.3) and answering (M = 1.93). They also have higher coding activity (M = 4499.5).

In Cluster 3, despite the high activity and communication on the forum (M = 5.21 for answers and 2 for posts), students still have grades similar to those in Cluster 1 and 4.

The least active group of students with overall below average activity comprise Cluster 2. Students have the lowest grades (M = 28.6) and percentage of completed tasks on the online course (M = 75.8) as well as low activity in RStudio server outside of the classroom (M = 57.2).

Cluster five is the least represented group of the most active students. Students have highest grades and are active participants on the Q&A forum. They prefer to answer questions and helping peers (M = 6.67) rather than posting questions themselves (M = 3.83). In this cluster, students’ usage of the RStudio Server is higher than in any other cluster, except for Cluster 3. Students also use R outside of the classroom more often, that can indicate these students as being engaged in the course and programming.

No significant differences between the students of different majors and the clusters were found, suggesting that these interaction trajectories may not depend on the previous background of students.

3 RESULTS

Table 1: Clustering results

<table>
<thead>
<tr>
<th>Variable/Cluster(number of students)</th>
<th>1(33)</th>
<th>2(33)</th>
<th>3(28)</th>
<th>4(93)</th>
<th>5(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>M</td>
<td>SD</td>
<td>M</td>
<td>SD</td>
<td>M</td>
</tr>
<tr>
<td>r_logs</td>
<td>4499.5</td>
<td>1940.0</td>
<td>3301.4</td>
<td>2274.1</td>
<td>6575.9</td>
</tr>
<tr>
<td>independent_study</td>
<td>57.3</td>
<td>10.1</td>
<td>55.1</td>
<td>11.4</td>
<td>61.8</td>
</tr>
<tr>
<td>stepik_percent</td>
<td>83.4</td>
<td>23.0</td>
<td>75.8</td>
<td>19.3</td>
<td>91.3</td>
</tr>
<tr>
<td>stepik_percent_wrong</td>
<td>43.7</td>
<td>0.3</td>
<td>50.7</td>
<td>0.6</td>
<td>51.2</td>
</tr>
<tr>
<td>forum_posts</td>
<td>2.3</td>
<td>2.3</td>
<td>0.6</td>
<td>0.6</td>
<td>2.1</td>
</tr>
<tr>
<td>attendance</td>
<td>11.6</td>
<td>3.8</td>
<td>9.0</td>
<td>4.3</td>
<td>12.3</td>
</tr>
<tr>
<td>forum_answers</td>
<td>1.9</td>
<td>1.5</td>
<td>0.0</td>
<td>0.0</td>
<td>5.2</td>
</tr>
<tr>
<td>grade</td>
<td>36.4</td>
<td>7.8</td>
<td>28.6</td>
<td>11.5</td>
<td>34.5</td>
</tr>
</tbody>
</table>

(LPA) model-based clustering employing Mclust library in R. In order to detect the optimal number of trajectories (here and later called clusters) Bayesian Information Criteria (BIC) was used.

To compare patterns of students’ activity between clusters we used Kruskal-Wallis, assessing if there is a significant difference between clusters at all in terms of academic performance, with Dunn’s post hoc test with Bonferroni correction for multiple comparisons.

4 SUMMARY

The paper presents the results of the analysis of student activity in a blended course. To identify learning trajectories, a mixture model was applied to cluster students’ data on the use of available resources in the course. The results of the clustering suggest the existence of five different learning trajectories with varied resource use in the blended learning settings and result in different academic achievements, showing that some trajectories can potentially lead to the more successful completion of the course.

Our current work is dedicated to a more detailed exploration of the trajectories and design of adaptive exercises [3] where educational materials are adjusted to the level of students.

REFERENCES


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Brug af mikrofeedback fra studerende, som supplement til LMS data, for at nedbringe frafald.

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Abstract:
Projektet søger svar på hvilke faktorer der kan udløse frafald blandt studerende på Niels Brocks online uddannelser. For at forstå de studerendes handlemønstre, vil der til projektet indhentes selvindberettede mikrodata fra de studerende via en simpel applikation hvor de studerende, ugentligt eller dagligt, bedes om at angive deres status vedrørende:

• Motivation
• Oplevet faglig forståelse
• Behov for hjælp
• Trivsel
• Arbejdspres og tidspres

Disse data kobles efterfølgende med LMS data på brugen af de digitale læringsmaterialer samt med de studieadministrative data. Som case analyseres data fra Niels Brocks 5 og 10 ugers online erhvervsuddannelser inden for kontor-, handel- og detailbranchen (EUS), over en 4 måneders periode. De kurser de studerende følger er 100% online kurser, inklusive eksamen. De studerende har en gennemsnitsalder på 27 år, kommer fra hele Danmark og har jobs og familier ved siden af. Frafaldet fra uddannelsen har i første halvår 2017 været på 23%.

Projektet indrager viden fra user experience (UX) feltet, og har således fokus på at et online kursus er et digitalt produkt. Dette produkt skal forstå som en helhedsoplevelse, der skal fungere for at den studerende fastholdes på studiet. Vi ved allerede, fra kvalitative interviews og spørgeskemaundersøgelser fra de studerende, at disse online kurser har en frafaldsproblematik der ofte er udløst af faktorer som:

• At de studerende ikke spørger om hjælp
• Tab af motivation
• Tidspres udløst af faktorer i privatlivet

Metode:
• Data fra LMS, studieadministrative data og data fra de studerendes mikrofeedback indsamles og analyseres dagligt. Data formidles til underviserne dagligt/ugentlig, således at underviseren kan henvende sig til de studerende, der på baggrund af data, vurderes som studerende værende i risikozonen for frafald.
• Projektet vil samtidigt undersøge effekten af- og formen på dataanalysen, der sendes ugentligt til underviserne. Her vil der være fokus på en visuelt overskuelig og interaktiv oversigt, således at underviseren nemt kan handle på disse data, indenfor 24 timer.

Keywords: self-reported student data, learning analytics dashboards, learning analytics implementation challenges, teachers-facing learning analytics, user experience
ABSTRACT

This poster explores how students’ attention levels in a learning situation can be traced through recordings of their electroencephalography (EEG). The EEG signals are recorded through the NeuroSky MindWave Mobile headset during lectures in the classroom. We deploy learning analytics methods, and we configure and aggregate the recordings to create visualizations for a prototype of a real-time dashboard.

This dashboard provides the students and teacher with neurofeedback information about the present attention levels in the classroom and will be used as a pedagogical neurofeedback tool to increase the students’ capabilities in controlling their attention and concentration in learning situations. Data and analysis from the first pilot tests are presented here.

KEYWORDS

EEG, Attention, NeuroSky, Multimodal Learning Analytics, Learning Design

INTRODUCTION

Students’ capabilities to control their own levels of attention and concentration are paramount for both the students’ learning processes and learning outcomes. It is also important in relation to students’ abilities to manage and control their own learning as described in the “Danish Qualifications Framework for Lifelong Learning” (DQFLL). This includes students’ abilities to self-regulate their own learning and the ability to control ones attention level is a fundamental ingredient therein[1].

The advent of consumer-grade and relatively cheap sensor equipment capturing EEG signals, provides new opportunities for using EEG data to measure attention. The NeuroSky MindWave Mobile Headset is such a low-cost brainwave sensor headset, which is set up to measure levels of attention and meditation.

In a recent study Poulsen et al showed the feasibility of recording students’ EEG in a natural classroom environment using commercial-grade wireless EEG devices[2]. Poulsen et al measured the students’ neural responses, while they were shown specific video sequences, similar to the approach developed by Dmochowski et al[3]. Their study reproduced previous results from laboratory settings regarding the measurement of students’ neural responses to media stimuli and found that EEG probably can be quantified from natural classroom environments[2].

This study investigates how students’ attention levels can be traced during the typical natural lecture in the classroom. We conducted an experiment, where we recorded such a lecture, while the students each were wearing NeuroSky MindWave Mobile Headset.

Electroencephalography (EEG) data are being collected from the NeuroSky MindWave headset. The headset is placed on the student and records EEG signals through one single dry sensor placed on the student’s forehead. Furthermore, the headset is connected to the left ear for reference and ground. The headset values for attention are based on Neurosky’s proprietary ‘Attention Meter’ algorithm. The headset records the EEG data in real time, and we collect the data as the students’ levels of attention. The output is measured per second on a scale from 0 to 100.

Our study relies on the one side on the aforementioned assumptions regarding the validity and reliability of the measurement of attention that has been confirmed to some extent by Johnstone et al.’s study[4]. On the other side, our study relies on that we in the video recordings can see the behavioral signs of high attention or low attention confirming the EEG measures, as well as the interviews with participants also underpins the EEG measurements.

This approach aligns with the field of multimodal learning analytics (MMLA), where the purpose is to capture and integrate learner related data from different sources in order to obtain a more holistic understanding of the learning process[5].

We synchronized the video recordings with the simultaneous recording of EEG data from the NeuroSky MindWave headset. Before the lesson, each headset is connected via Bluetooth to the student’s laptop computer. During the lesson data are sent from the laptops to Micro Azure services, e.g. data is persisted in a document database. Furthermore, we developed a framework for the EEG data collection in order to collect and synchronize the measurements from the individual headsets.

In this pilot study, we collected data from four sources: 1) EEG data from the headsets, 2) video recordings in the classroom, 3) individual interviews with selected students and one focus group interview, and 4) an individual interview with the teacher.

The EEG data was looked through for peaks, and we selected three peaks as basis for the interviews. The peaks were consistent with the sights in the video recordings and were also underpinned with the students’ statements in the interviews.
The interviews had the purpose of understanding and pursued the students’ immediate experiences of the importance of the actual teaching in the peaks, and the students’ own individual opinion of their levels of attention in the peaks. The preliminary findings showed consistency between the students’ experiences, the sightings in the video recordings and the EEG data in the three selected peaks. These findings will be further investigated.

REFERENCES


Developing a Learning Analytics tool

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This poster describes how learning analytics and collective intelligence can be combined in order to develop a tool for providing support and feedback to learners and teachers regarding students self-initiated learning activities.

In 2013 the Danish university college sector began the implementation of the Study Activity Model (SAM). SAM should “provide for all programmes a single academic tool which can shape the study expectations of the students in relation to study intensity” [1]. The model is divided into four categories describing study activities as: 1. Participation of lecturers and students – initiated by a lecturer, 2. Participation of students – initiated by lecturers, 3. Participation of students – initiated by students, and 4. Participation of lecturers and students – initiated by students. Our interest has been focused on the third category in which the students must initiate learning activities by themselves, without the teachers being part of the activity. Student surveys indicate that time spend in the third category is generally lower then anticipated. This is also confirmed by our interviews conducted in 2016, with students from different educational programs, where we found different reasons for this [5]. For the students (a) it can be difficult to relate activities in their spare time as a part of their study, (b) they do not feel that the education/teachers appreciate their effort, and (c) activities are not embraced as a part of their education. Based on previews work [4] we are now designing a tool that supports the students in reflecting on their study related learning activities and in getting inspiration from other students learning, and helps the teachers becoming aware of study related learning activities and making activities a part of other categories in SAM.

Supporting self-initiated learning activities in an educational context could be done in many ways. Based on the assumption that learning can happen through reflection, our approach takes into consideration reflections through drawing relationship among learning goals, intended and actual outcomes and experiences. The student should be able to do this in cooperation with peers. The aim of the project is to develop a data integration and visualization tool – a tool that can handle connections between students, learning activities, learning objectives etc. can be the solution.

The method for our development process is Design & Development Research (DDR). DDR describes the research process for developing information technology products or artifacts [2]. The DDR process is divided into six steps as shown in fig. 1. Currently our development process is somewhere between step b and c. We have the objectives in place after researching the overall problem. Now we need to get a clear idea about the detailed requirements and the design for the tool. One method we can use in this process is the Learning Analytics Model (LAM).

LAM is a model for describing a systematic approach to analytics into different components (fig. 2)[6]. The process described by LAM is iterative. The actions that is performed at the end (last step) will influence on the collection of new data (see later about feedback).

Developing on top of LAM we will introduce Collective Intelligence (CI) as an important part of our system. CI is the idea that, supported by the technology, people can benefit the from the synergy of the collected effort [3].

Figure 1: DDR process [2]
From a LA perspective CI can extend the basic idea of LAM by bridging between collecting data, displaying data and student actions. In a social software, actions forming feedback to the system can be both implicit and explicit. Analyzing both on the students input (the creation of entities) and the way that they use the system (statistics about the use).

Pushing forward the development process of our tool, LAM is a useful model, then we need to describe the different components of the analysis. Together with the concept of CI, LAM will sharpen our focus on making the tool useful for students and teachers.

Bibliography


Skedsmo municipality has the ambition to exploit these insights in their own educational context. Together with the EdTech company we will develop a solution for how to connect online learning activities to the asynchronized information displayed in Conexus Vocal (dashboard for teachers). This project will utilize an existing learning platform-and adapt asynchronized learning tool into a reading competence framework developed for children in primary school/K-12. In order to exploit analytics as an instrument for reflecting current pedagogic practice and for validating didactical patterns, we will explore the possibilities that come with dashboards based on Learning Analytics (LA) and designed within a pedagogical framework, to improve teachers’ knowledge of pupils reading development and their teaching.

Recognizing the importance of contextualization of learning data resources with a broader set of indicators to understand the learning process, it’s found that children often use different learning approaches when using digital learning resources (Gašević, Dawson & Siemens, 2015). We will use this framework of self-regulated learning (SRL) and motivation when developing and evaluating the digital learning tools in this project.

The innovation in this project is to incorporate a reading skills program based on reading development focusing at improving pupils reading fluency and comprehension in 4th to 6th grad. The project will follow development of the reading tasks and together with Conexus follow the developing of dashboards and its pedagogical use. Furthermore, we will follow the use of the learning tools directed by the theoretical framework of SRL and goal orientation theory in authentic classroom setting.

Introduction

Despite decades of research into teaching and learning, we still know very little about how pupils learn. New digital technologies in the form of interactive learning analytics represent a potential to advance this understanding. In close collaboration with the school sector and the Edtech sector this project aims at developing and implementing an innovative learning analytics tool in primary school.

This project ought to evaluate and develop teacher driven criteria’s for facilitating teaching for pupils with different prerequisites in reading, and to detect those children who struggle with or has stagnated in their reading development. We will utilize an existing learning platform-and adapt a synchronized learning tool into a reading competence framework developed for children in primary school/K-12. The innovation will further incorporate the reading skills tasks from a set of competence defined needs based on reading development considering the age of the present sample designing different learning tools, focusing especially/aimed at improving pupils reading fluency and comprehension is important (Wise et al., 2010)

Theoretically driven research can bring in more cumulative knowledge in learning analytics. This can be the case in where its identifying mechanisms underlying how a specific learner uses the learning tool (Rogers, Gašević & Dawson, 2016). Using the theoretical approaches from learning approaches from self-regulation theory (Winne and colleges, 2006) and motivation (Elliot, Murayama & Pekrun, 2011; Kaplan & Maehr, 2007) we will investigate how children uses different learning approaches when using digital learning recourses.

Research aims

Firstly, taking the perspective of teachers understanding of how to target children’s reading development (guided by prior research on reading and reading comprehension) they will together with the Edtech
company and the researchers develop a solution for how to connect online learning activities to the asynchronized information displayed in Conexus Vocal (dashboard for teachers).

Second, the researchers will apply a measurement of differences in pupils SRL and motivation in association with reading skill enhancement and analyse the use of the learning resources.

Third, the project partners will investigate the effect of incorporating online synchronized learning tools into core school activities, and evaluate the overall benefit of such a collaboration

**Methods**

**Population:** 4th to 6th graders in Skedsmo county.

**Implementation:** Teachers will define the learning tasks in reading and together with Conexus developing the digital learning tool, and the researchers. The development of the dashboards and its pedagogical use will be directed by the theoretical framework of SRL and goal orientation theory

**Questionnaires and tests:** We will conduct additional questionnaire to those pupils included in this study to measure language skills and development throughout the school year. We will test language skills before and after the implementation of the reading program.

**Discussion**

The primary objectives in this project is to ensure that the schools in Skedsmo municipality are given access to information about pupil’s behaviour that has not previously been available. This will enable the teachers to better understand and monitor students reading development. It will also give a better tool to detect reading problems and teachers to adjust and personalize their teaching, and to advance communication between children, teachers and schools.

Skedsmo municipality has the ambition to exploit these insights in their own educational context, and if successful, making the innovation available or upscaling to schools on a national scale (and beyond). In addition, we will evaluate how to initiate and integrate digital learning tools in schools in a sustainable way.

The innovation will enhance improved services for teachers and children in visualizing children’ learning by dashboards/tools based on learning analytics. The opportunity in this project is to use technology that collects, organizes and analyses various sources of data to developed suitable interfaces that may support teachers in their pedagogical work. The innovation may be further refined and spread to primary schools in Norway.

**References**


Optimism vs. Realism in Learning Analytics:
Answering the ethical questions is the hard problem

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Abstract

From an educational perspective, one of the most important trends of the 21st century is the massive digital transformation of public education. The digital transformation radically changes the ways students, educators and institutions behave and interact, and it results in vast amounts of data generated in the digital systems in which the new behavioral patterns unfold.

This development has led many policymakers to believe, that a breakthrough in the use of learning analytics techniques in public education is imminent. The immediate success of e.g. the Google Flu Trends projects has supported this belief, and even though it turned out that the accuracy of the predictions wasn’t as high as expected, the optimism has remained intact in the sense that there is strong confidence that it’s merely a question of solving technical problems.

However, as the interest of using analytics techniques has been applied not only to education administration, but also to student behavior and learning environments, it has become apparent that even though solutions for technical problems might be within reach, learning analytics is still facing the hard problem, namely answering the ethical questions that arise in relation to the use of learning analytics in public schools.

The presentation discusses findings from a recent project on data visualization in digital learning environments. The main question was how students, teachers and other professionals could benefit from the investments in digital learning platforms and digital learning resources. As the project evolved, however, it became clear that one of the main obstacles to success was access to data. Not because of lack of data format standards or other technical issues, but because harvesting data in public schools raises a host of ethical questions to which we don’t yet have the answers.
Poster: Using Epistemic Network Analysis to understand core topics as planned learning objectives.
Benjamin Brink Allsopp, Jonas Meldgaard Dreyøe, Morten Misfeldt

Epistemic Network Analysis is a tool developed by the epistemic games group at the University of Wisconsin Madison for tracking the relations between concepts in students discourse (Shaffer 2017). In our current work we are applying this tool to learning objectives in teachers digital preparation. The danish mathematics curriculum is organised in six competencies and three topics. In the recently implemented learning platforms teacher choose which of the mathematical competencies that serves as objective for a specific lesson or teaching sequence. Hence learning objectives for lessons and teaching sequences are defining a network of competencies, where two competencies are closely related if they often are part of the same learning objective or teaching sequence. We are currently using Epistemic Network Analysis to study these networks. In the poster we will include examples of different networks from a corpus of learning objectives from a project, “The goal arrow”, developing a prototype learning platform (Misfeldt et al 2015).

The analysis suggest a two dimensional space of mathematical competencies where one dimension is characterised by having communication at one end and mathematical problem solving at the other, and the other dimension is characterised by a dimension going from thinking to articulation. The poster will include analysis of networks for grade 1-3, grade 4-6 and grade 7-9 using these dimension to suggest a way to look at the progression in mathematical competence focus in Danish compulsory school.


Looking at Learning at Larger Scales

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How can a Learning Analytics architecture be built and applied to address challenges in Higher Education?

(Initial focus on combination of data: Semantic and technical interoperability)

Abstract

We are developing a Learning Analytics architecture to address challenges in Higher Education. Parts of this project will be carried out in cooperation with the Center for Big Data Analysis at Research Computing. The Learning Analytics architecture will enable data collection and storage, computational data analysis, and reporting of insights to stakeholders at different levels.

Educational Data

Different types of data are generated about learners in Higher Education. Sources such as Learning Management Systems, Student Information Systems, assessment tools and social media are available in digital spaces. In addition, data are increasingly being collected from physical spaces through the use of diverse sensor technologies.

Semantic Technologies

By employing semantic technologies to enable shared meaning among data, we will combine data that come from different sources, with varying levels of structure, and which are originally stored in different formats. This work will draw upon standards for educational data, such as xAPI.

Systematic Review

At the current stage of research the focus is on collecting and integrating data. The aim is to enable more useful computational data analysis through the availability of larger scale and more diverse data.

This poster describes the systematic review of data sources used in Higher Education that we are conducting. Of interest is how and to what extent multiple sources are combined in existing research. Academic databases have been searched with the following string:

```
("multiple data sources" OR multimodal OR "multi-modal"
OR "multiple data sets" OR "multiple datasets")
AND ("learning analytics" OR "educational data mining")
AND "higher education"
```

This review will provide important foundations for the architecture and identify gaps in the literature.
When Learning is High Stake
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ABSTRACT
Fire fighter learning is high stake. They need to maintain certain competence levels related to physical, mental, and firefighting and rescue skills in order to provide the public with a high level of emergency service. Fire and Rescue Services need to maintain an overview of the current competences of their personnel and to react when there is a competence gap. This poster presents our approach to using competence modelling, learner models, learning analytics, and visualisations in order provide insight into competence status and development on the individual, team, and organisation level and to provide early-alerts and automated messages to instructors responsible for planning training activities, and to team leaders responsible for making decisions about teams in high stakes situations.

CCS Concepts
•General and reference→ •Empirical studies •Information systems→ •Decision support systems •Human centered computing→ •User models •Visual analytics •Applied computing→ •Education •Social and professional topics→ •Model curricula •Student assessment •Adult education •Testing, certification and licensing

Keywords
Learning Analytics; Competence development; 4C/ID; Open Learner model; Visualization

1. INTRODUCTION
Can learner models and visualisation of competences, for individuals, groups, and the organisation as a whole, help to improve decision making about training needs? As part of an increasing trend towards an evidence-based policy, the EU policy objectives promote standardisation of competences through the European Framework for Key Competences for Lifelong Learning [1]. This is a reference tool for EU countries and their education and training policies. Norway is no exception and has a focus on careers such as a carpenter or mason. Modern organisations need to follow the trend and have a continuous focus on education and training. Still many institutions and organisations experience challenges in collecting and analysing information about learners, and groups of learners.

Maintaining an overview of competence status and development in the organisation is needed in order to make informed decisions about learning, teaching, management, and organizational development. The Fire and Rescue Service (FRS) is an example of where the need of such overview is crucial, both at an individual employee level, at a team level, and at organisational level. In Norway, potential fire fighters are recruited from vocational schools with a focus on careers such as a carpenter or mason. FRSs are themselves responsible for the education and training of these potential fire fighters, and are further required to ensure that the fire fighters maintain extreme skills and meet intensive fitness standards. This is not only related to the two years of training to become a fire fighter, but continuously throughout their entire career.

2. PERSONNEL, EQUIPMENT AND COMPETENCE TRACKING
The iComPAss project [2] seeks to develop tools and methods that can increase the ability to assess and identify competence gaps in order for instructors to make decisions about instruction and competence development before they become problematic. We support this by drawing on learner models [3], competence modelling, assessment, performance evaluation, and learning analytics. Our approach builds on the research from two previous EU-projects (ADAPT-IT and Next-Tell), and on the partnership between Sotra Fire and Rescue Service (SFRS) and a software company, Enovate AS, both situated on the west coast of Norway. SFRS uses a competence tracking and training activity planning tool called ADAPT-IT (Figure 1) developed by Enovate AS.

Figure 1. ADAPT-IT overview of equipment, exercises, tasks, personnel, and teams
ADAPT-IT addressed the challenges associated with keeping track of planning of training to meet the competence needs of the fire and rescue service. The tool was designed to assist the end users to collect and document key information using a mixture of web-tools and mobile apps. By using the tool the management has access to a web interface that is constantly updated with an overview of the competence status of their fire department. ADAPT-IT was tailored to improve the planning of training and documentation for fire departments by incorporating streamlined competence control, planning, crew and equipment, deviation in-app reporting using voice and media, combining assessment tools that inform on relevant required competence needs. Reports from the instructor describe how the tool is used in planning of all the departments’ training.

In iComPAss we addresses how to harvest data from assessment situations on readiness for incident action, training situations, and performance in real life incidents in order to develop learner models and form the basis of visualisations of the current situation that support inquiry [4, 5] for decision making in high stake situations.

ADAPT-IT helps the instructor to keep track of the needs in the entire organisation according to the requirements of the different roles. In an interview an instructor at SFRS described how the tool is used in planning of all training activity in the department. ADAPT-IT maintains a competence profile (a learner model) for each member of the fire brigade, which is updated with assessment data about the competences from training situations, from certification information, formal knowledge quizzes, etc. We are implementing a Competency Gap Analysis (learning analytics) on the learner models that supports the instructor in planning training activities and the renewal of certifications by providing early-alerts and automated messages when particular situations are discovered. This enables the instructor to be proactive and invest in training, courses, and certification of the personnel as needed. This is done by:

1. collecting assessment data from exercises and real fire and rescue situations, on identified competences
2. using defined criteria for collected information in order to visualise the competence profile through histograms and spider graphs.

Furthermore, the planned analytics functionality of ADAPT-IT will also provide visualisations that enable a team leader to make real-time decisions about team constellations when responding to an incident (Figure 2).

3. CURRENT AND FUTURE WORK

It is crucial for fire fighters to have the needed competences to perform the risk intensive tasks required of them in a variety of fire and rescue situations. As a member of an incident team the fire fighters have to trust all members to have the needed competences. Therefore, it is crucial for the instructor to have an overview of the training needs in the department. For example, interviews with fire fighters and leaders identified a need to be able to report on readiness for smoke diving. In order to collect readiness data where fire fighters reporting for duty answer questions related to mental and physical readiness and a question about their availability to smoke dive, a readiness app is under development. In the app the team leader will be presented with a dashboard that supports the assignment of fire fighters to the required tasks in a response situation. The data collected by this readiness app needs to be supplemented with data from the learner model, data such as certification status, performance on particular tasks, competence levels, etc.

Use of technology for learning in the workplace has increased the amount and variety of electronic data available for use in learning analytics and visualisation. Therefore it is also important to study how people use this information. We will build on our earlier work on a framework for data literacy and use for teaching [6] and learning (REF TO LAK16??) as a step in exploring how the collected and visualised information is interpreted and transformed into new practices.

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5. REFERENCES


Readiness App: Data Collection for an Open Learning Model and Learning Analytics

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Abstract

Some occupational groups, such as firefighters, have job tasks that can directly affect their own or others’ lives and health. In order to carry out such tasks, higher demands on day-to-day preparedness and certifications are often required than in other occupational groups. In this Masters research, which is part of the iComPAss project, we have considered how technology can support emergency leaders in a fire department to ensure that the best qualified personnel are used for the most critical tasks. In the fire department, smoking diving is considered to be the most critical, and physically and mentally demanding task. The term readiness has been used to describe the momentary status of firefighters to do their job, and it there is a distinction between physical and mental readiness.

After interviews with the fire chief, and analysis of the fire service, a mobile application was designed and developed to enable firefighters to report daily their own readiness for the job. This includes both physical and mental readiness. Data about the crew's readiness and certification status is visualized and presented on a Dashboard for Emergency Leaders in the same application. This data becomes part of a larger collection of data sets about the firefighters, and learning analytics is used to interpret the data sets in a larger perspective.

An iterative design process was used, and the app was developed according to principles of flexible methods and interaction design, with a high degree of focus on visualization and user experiences. To ensure good design, an heuristic analysis of the application was carried out before it was finalised. The figure under shows the final two options for the main screen of the Readiness App. The app is being tested with the firefighters as part of the iComPAss project.
Can the use of learner models, LA and visualisation support instructors and fire fighters for better overview to identify competence gaps in order to improve inquiring processes about training needs?

Harvested data from the assessment app forms the basis for visualisations of the competence situation to support inquiry for decision making about training & organisational development. The visualisations show the competence status of individual firemen, a team, or the entire fire brigade.

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