Immersive Smart Learning Environments – Schriftliche Ausarbeitung: Vortrag in Textform

Tom Gülenman

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Organisatorisches

- Studienfach: Informatik Bachelor, FU Berlin
- Modul: Wissenschaftliches Arbeiten in der Informatik
- Studienordnung 35/2014

Ausarbeitung

In recent years, technological advances such as the Internet of Things have not go unnoticed, but most of the times we hear about them, they are not being associated to the sector of learning. I will present an overview on how an evolution of learning spaces is enabled nonetheless. I will talk about how learning has evolved in the last years and how it can evolve in the future. For that matter I mainly studied the five papers listed below, to whom I will refer as paper 1 to 5 further on.

1. Yacine Atif et al. (2014) Building a smart campus to support ubiquitous learning
2. Yacine Atif et al. (2017) A Cyberphysical Learning Approach for Digital Smart Citizenship Competence Development
3. István Koren, Ralf Klamma (2016) Smart Ambient Learning with Physical Artefacts Using Wearable Technologies
4. István Koren, Ralf Klamma (2017) Community Learning Analytics with Industry 4.0 and Wearable Sensor Data
5. Jan Schneider et al. (2014) Augmenting the Senses: A Review on Sensor-Based Learning Support

Let us jump right into it by looking at what we call Ambient Learning Space.

In my opinion, this concept is understood best if explained by an example: a chemistry lab on a Smart Campus. We will talk about Smart Campuses later, but for now we just stick to our laboratory. In this chemistry lab, we find numerous resources like books, test-tubes, weighing balances etc. Our lab might even be split into multiple parts around the campus and with it its resources. By augmenting those resources, thus connecting them to a campus wide network, we can know the details of their functionalities and their availability at all times. That way, it is also possible for faculty members, that are associated to the lab, to define schedules and restrictions on those resources. Therefore, Ambient Learning Spaces are environments where one or more physical learning resources are digitally and socially augmented, thus interconnected using Web Services. That means on one hand we have augmented objects in a network of similar resources that is extended every time a new, let's say, a weighing balance, is commended.

On the other hand, we have faculty members associated to the learning spaces and therefore to learning resources. In our example, the ordered balance would at first look for its own kind in the ALS, which is done by comparison of similarities to clusters of resources, and then send friend requests to faculty members already associated to similar devices. Only then it can be used to schedule experiments for students.

All of this is representing a very formal learning context, to which we will stick for now, but we will see later that similar concepts are suitable to informal learning contexts as well. Now that we have a first understanding of what an ALS can be, allow me to give you an outlook on the learning contexts to come: Firstly, we will deepen our understanding of the Smart Campus, secondly we will see how Learning Environments and Smart Cities fit together just before studying aspects of the broad topic of sensor-based learning with specials attention to wearable technologies and Industry 4.0.

Let us stick to the Smart Campus for now. The development of a Smart Campus tries to give an answer to the question: What can be done to make learning the formal context of a university better by exploiting modern technological advances? The two innovating main aspects of a Smart Campus we want to get a better understanding of are: it being a composition of Ambient Learning Spaces like the chemistry lab we have just talked about and the development of personalized learning agendas.

But why are those personalized learning agendas a good thing? Not all students share the same knowledge, interests and affinity to all topics. The concept of ubiquitous-learning, or u-learning, which stands for the idea of a campus-wide social network enabling learning the right information at the right time, permits context data to influence learning paths and hence on learning agendas. And how does it work? Driven by lots of social interactions with peers, instructors and learning objects, learner profiles will be created. Those profiles contain information like goals, competences, interests and other that can be studied to adapt the proposed services on the Smart Campus and with it the learning agenda.

To ease the assignment of learning resources and services, the PLOM standard is introduced. The pervasive learning object metadata describes the content and context of learning resources. This metadata helps the Smart Campus system to autonomously include the virtual and physical learning resources. The weighing balance from our example is a PLOM-Object and all similar devices in the lab are a cluster of PLOM-Objects. Clustering those objects is essentials as it builds the foundation of Ambient Learning Spaces. Clusters are represented by their respective centroids and indicate what objects and services should be used at which learning stage.

A prototypical implementation of a network that autonomously clusters PLOM-Objects has been tested with multiple clustering approaches and led to promising results. The authors of the first paper indicate that experiments within a university campus are planned.

Let us move on to a rather informal and heavily context-dependent learning environment: Smart Cities. What is a Smart City? It can be defined as a possible solution to new challenges due to growing populations and the degradation of the environment. It uses digital technologies to enhance its functioning and to engage with its citizens in a surprisingly similar way to the Smart Campus.

Living in a Smart City means adopting new sustainable lifestyles by exploiting those digital technologies. Being able to tell which appliance in your Smart City home used how much energy and adapting new styles of usage to preserve the environment are one example for so-called digital smart citizenship competences. It is only logical that such innovative lifestyles require new kinds of learning approaches, that we call Cyberphysical Learning and that combines situational learning with augmented learning experiences.

Let us look at an example, where we focus on the energy consumption of a washing-machine that represents our cyberphysical learning environment. The learning goal of the following use case is increased awareness on the value of energy of the user.

First of all we need to know about power data. That means a visualization of the energy consumption of the washing-machine in the recent past in particular scenarios and in hypothetical scenarios such as ‘how much energy would we need if we used the appliance at an alternative time or mode‘. That is what our first competence ‘energy use data‘ is about. The second competence we learn about is the energy use footprint. What this means is that we would be able to learn about the global realized and forecasted energy consumptions and access those informations via our personal devices such as smart phones. Not exceeding a given energy threshold across all appliances with the help of warnings and combinations of programs represents the third and last competence: energy use control.

In this example, we have seen that it is also made usage of learning paths as in from getting feedback to undergo behavioural changes. Those learning paths are also associated to learner profiles. To conclude on Smart Cities, we can say that they rely on their inhabitants' engagement and therefore depend on the success of context-dependent learning methods, in which citizens use their smart citizenship competences to feedback on their lifestyles and make changes to them if needed.

In this next part, we will study another situation-dependent and informal learning context: Sensor-based learning and more specifically wearable technologies. The name already gives it away: wearables are smart devices that can be worn on the body and are therefore ideal in workplace situations. They are constantly available and able of augmenting physical artefacts like we have talked about it before. As they are always with its user, wearable technologies can provide a good understanding of interactions between learners and their environment. We call this understanding Community Learning Analytics.

Let us look at some more examples. In the construction sectors workers are confronted with a large variety of materials and tools every day. Using their Smart phone or other Smart device, workers can get a list of today's tasks and tools needed. For those tools, video tutorials are available and new videos can be recorded and commented. Smart helmets that grant 360 degrees vision amongst other things are another example for potentially useful wearable devices.

To get to this point a number of challenges has to be passed first. Wearables need to be aware of physical artefacts around them, that then need to be identifiable, obviously. Some of the technologies that help the service discovery are QR-Codes, Near Field Communication and Bluetooth Low Energy, that are already used in credit cards, Smart phones and tablets etc.

Another very interesting use case is the Exhibition Concept presented in the third paper, which is about museum visitors using their smart phones as tour guides. They are able to scan exhibition items for more information and the possibility to save links to the physical artefacts for later use. A personal library system for PDFs, videos and audio is available. Visitors may also start a discussion with other visitors by commenting on the additional information provided. This greatly extends the dimensions of exhibitions, since new ways of looking into the exhibition subjects before, during and after the visit are suggested. A prototypical implementation of those features has been realized and was scheduled to be tested right after the publication of the paper. The authors also point out different challenges associated to the legal system, such as data ownership, privacy and intellectual property, that are extremely hard to resolved. An example of a privacy concern is the knowledge of the location of workers at all times, which could also enable new possibilities for burglars.

We will now deepen our understanding of wearable sensors and Industry 4.0 in the context of community learning analytics. We already know that mobile devices help us analyse the interactions between learners and entities in informal learning contexts and the same goes for interconnected Industry 4.0 production machines. What we don't know yet is how to methodologically use and analyse this data. Even more so, because the data we get from a multitude of different sensors and machines is highly heterogeneous. Since we can not expect those structures to become lighter in the near future, we need a sustainable solution to approach all relevant data.

One solution proposed is SWEVA, the Social Webbased Environment for Visual Analytics, containing services able to retrieve data from heterogeneous, visualizing it and identifying experiences users of machines and tools and visualizing their output to less experienced users. The crucial part is that all of the above is dynamically done in near real time.

Using mainly open Web technologies, retrieved data runs through 5 stages: The Data Source level is where the data is captured. The aggregation level is where data is stored and heterogeneous data is stored in common IoT databases. Moving on, we create and edit models, that define our visualization, consisting in directed acyclic graphs and then execute it in the core framework. The visualization tool displays the results, provides the UI elements and calls the framework again in case of input changes made by the user. (For an example, please refer to slide 14/22 in the associated presentation).

The fact that mainly web technologies are used in this process makes this analytics tool highly compatible, accessible and reusable. The system has been tested with an IoT Dataset of thousands of weather station measurements during hurricane Katrina in 2005 and for 70 nodes it still managed to have 30fps. And what does that mean? It means that the sensor data of 70 weather stations during the hurricane were read, interpreted and displayed in near real time at a frame-rate of 30 per second. For 110 it dropped to 20fps.

Remaining challenges were again in the sectors of privacy and moral questions but also data quality. Furthermore, the authors indicate that machine learning could be used to further automate analytics.

Let us now take a closer look on data sources, notably the evolution and usage of sensors in the domain of learning. In this context, sensors represent physical or virtual objects used for tracking, recording and measuring. If we couple sensors with software we get tools that immediately show us the results of the obtained data. These sensor-software combinations are referred to as sensor-based platforms. Of most interest to us here is how those sensor-based platforms can assist the implementation of formative assessment which means to check for a learners understanding while the learning is happening. To do so, 79 sensor based prototypes in existence have been studied and classified into learning domains and whether they implement formative assessment and give feedback to the user or not.

The majority of prototypes aim to help the user to remember facts, understand concepts and analyse situations and are therefore classified as belonging to the cognitive learning domain, while 17 belong to the psychomotor domain, helping to improve physical abilities and only 6 aim to engage the user in specific activities. Allow me to quickly slip in one example for a prototype: amongst the studied was a sensor-based platform that monitored the movements of its user, after a heart stroke and was associated to the cognitive domain. 51 prototypes contributed to aspects of formative assessments and 35 gave feedback. But why is feedback so important?

Feedback can answer up to 3 important questions. The first one being 'Where am I going¿ as it tracks goals of the user; one example being a prototype visualizing the user's lifestyle as a virtual garden whose condition depends on the user's healthy or unhealthy life choices. The second question being 'How am I going¿. Feedback tracks actions and compares them to defined rules. As an example there was a prototype comparing the user's movements to those of a martial artist expert. The last question to answer is 'Where to next¿. Feedback can give advice on the next step to take, as in personalized learning paths, that we have talked about.

We can conclude that sensor-based platforms are very well capable of giving effective feedback by answering the questions we have just seen and by retrieving and evaluating personal information that is considered essential for formative assessment, but, interestingly enough, no prototype was able to answer all 3 questions which shows obvious room for improvement. The acquisition of source data useful to the learner and its presentation represent the two main research branches for sensor-based learning support. With a little more progress in these fields, the workload of teachers may soon be lowered concerning formative assessment with the help of sensor-based learning support.

Overall we have seen that new technological advances such as the IoT bear the potential to revolutionize learning in formal contexts such as in Smart Campuses composed by Ambient Learning Spaces, but also in informal contexts such as situation-dependent learning in a Smart Home or in workplace situations. By digitally and socially augmenting physical objects, we do not only create new opportunities, but also face new challenges, notably the autonomous exploitation of digital technologies in various ways.

Possible solutions to parts of these challenges have been presented by defining frameworks for ubiquitous learning, by proposing learning approaches for cultivating Smart Citizenship Competences, by analysing the interactions between learners and objects in informal learning contexts, by introducing a visual analytics tool to use the data generated from said interactions and finally by analysing the state-of-the-art of how sensor-based platforms can assist the implementation of formative assessment.

We can be assured that the future of learning will be shaped by the mentioned technologies but we absolutely need to be careful not to push innovation and progress faster than we can solve associated issues in the legal system and answer associated question of moral and ethical nature, in which I see a realistic danger, since also the authors of the papers studied were not able to propose solutions for these issues and as discussed, certain legal models are just being created and with those models being different from one country to another, developers and users of the technologies reviewed will face the challenge of an inconsistent market.