Exploiting Human Signals in Learning Environment as an Alternative to Evaluate Education Performance

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Abstract. There is a demand for new ways to understand the relation between student and group behaviour, and their impact on education performance. For that, we are researching, developing, and testing technologies to instrument classrooms, collect human signal data, and derive meaning that leads us to understand their relation with the education performance. We call this setup as "the Smarter Classroom". It integrates (i) applications running on tablet computing devices that play digital education content and collect students' gestures whilst manipulating the materials, (ii) environmental sensors such as video cameras and microphones, and (iii) innovative Analytics models that can make sense of these signals. In this work, we describe our development, present a practical experiment, and discuss the field applicability of this technology.

1 Introduction

The role of the modern education system is to provide students with skills and knowledge to prepare them to pursue advanced degrees and employment to be able to succeed in a globally competitive world [5]. This means that institutions must tailor learning experiences to their students towards the ideal of massification with personalisation of the education process. For that, there is a demand for new ways to understand the relation between student and group behaviour, and their impact on education performance.

We are developing learning environments that collect and store the *human signals* [10] generated during the learning process. We call this development as "the Smarter Classroom". It provides comprehensive and affordable instrumentation of classrooms along with innovative Analytic models that can make sense of this data. For example, we analyse signals like the time spend on a page, clicks, zooming gestures, taps, ambient sound, disturbances in the classroom, and others. Based on this information we can deduce individuals' behaviours like interest, attention, focus thought, and others [9], as well as insights on group behaviour.

The solution integrates (i) applications running on tablet computing devices that play digital education content and collect students' gestures whilst manipulating these materials, (ii) environmental sensors such as video cameras and microphones, and (iii) Analytics models to make sense of the data being collects. For the latter, we are exploiting the concepts of *Social Analytics* [1] and *Learning Analytics* [4] aiming to create the intelligence to:

– Classify individual and group behaviour based on human signals in learning environments.

– Correlate social behaviour to education performance.
– Recommend actions to improve the education performance, as for example adjustments in the learning environment, modifications in he content, distribution of students based on social roles, and others.

The paper is structured as follows. Section 2 describes the motivation and related work. Section 3 presents the prototype implementation and practical experiments. The paper concludes with Section 4 with an analysis of the results and a discussion about the field applicability of this technology.

2 Motivation and Related Work

We aim at tools to integrate the pillars of the education environment, *i.e.* teachers, students, the classroom, and planning. Our proposal is to create new methods to track and evaluate the students' performance taking in consideration how they interact with the education material, and with other students.

In the field of *Ambient Intelligence*, the work by [8] introduces an integrated architecture for pervasive computing environments in *Project ClassMATE*. The work in [11] proposes the use of sensors and speech recognition integrated to an analysis model in *project iClass*. The report in [2] discusses the opportunities and consequences of applying these techniques in the classroom environment.

Related to *Learning Analytics*, the report in [4] presents diverse approaches for the measurement, collection, analysis and reporting of data about learners and their contexts. The work in [12] provides a broad view of the use of Analytics in education environments. The work in [3] introduces Social Learning Analytics by combining learning analytics and social networks.

Moreover, we are motived by the work in [9], where human signals are collected and analysed to read people, allowing to classify individual and group behaviour, social roles, patterns in group interactions, and the development of social networks, and others.

The related work identified in the prior art provide the basis for the study being conduced in this project. We seek an integrated solution that exploits the concepts of data collection and environment iteration in *Ambient Intelligence* and the methods to extract deep insights provided by *Learning Analytics*. However, we want to use human signals as the reference data – instead of simply using exams' marks or surveys like usual analytic models in the latter. Hence, we identified an opportunity to contribute with a combined model as outlined below.

3 Prototype and Experiment

Figure 1 depicts the solution overview of the Smarter Classroom. It contains (1) *Front-end solutions* to instrument classrooms environment, *e.g.* with video cameras, voice capturing, ambient sound capturing, and applications running on tablet computing devices that play digital education content. For instance, we prepared a scenario where the teacher is equipped with a headset and a tablet computing device with a special control application. The teacher's voice is streamed to an Automated Speech Recognition

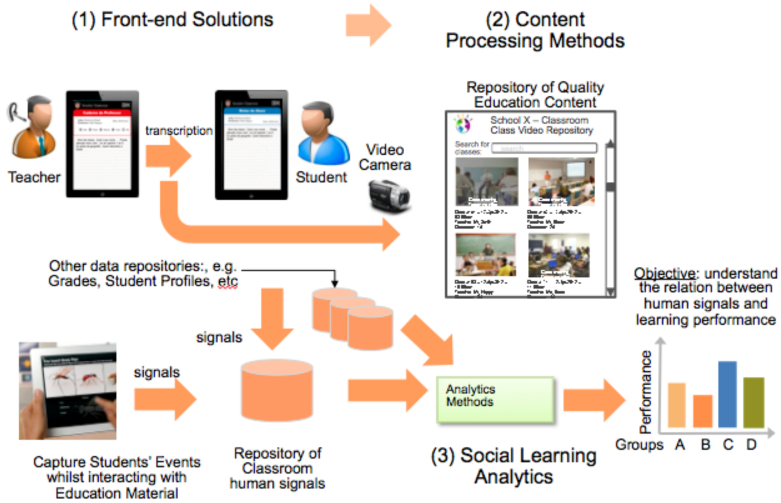

Fig. 1. Solution Overview: Smarter Classroom

service, generating the transcription. This is streamed to the students' tablet computing devices, creating a on-line annotation system. We also instrumented the classroom with a camera so to record the class. The content player was developed as a version of the Cool Reader [7], which is an open source e-book reader for Android. It is capable to handle standard formats like EPUB and FictionBook. The code has been instrumented to capture the signals, and store the data in log files. We represent a signal s_i as the tuple $< ts, tp, pr >$ where ts is the timestamp, tp is the type (*e.g.* page turn, zoom in, zoom out, link clicked, others), and pr are description parameters. At the end of the class, the applications upload the log files to a server where they are stored and indexed.

The environment also provides (2) *Content processing methods* to compile the captured data, making it available to other systems, students and administrators. In the sideline, we are exploiting this module to integrate with Content Management Systems in order to create dynamic web sites and repositories of quality education material.

Finally, the (3) *Social Learning Analytics methods* implements the models to derive meaning from the collected data. It works by a combination of calculation models in form of mathematical and statistical functions that process the human signals captured by the (1) *Front-end Solutions*.

For instance, let us say that: $M = \{m_1, \ldots, m_n, t_1, \ldots, t_m\}$ is the education material composed of the set of elements m_i (*e.g.* (text, figures, links, etc) and multi-choice test t_j, and the $S_{\{c,M\}} = \{s_1, \ldots, s_n\}$ contains the signals captured from a student c using M. The classroom $C = \{c_1, \ldots, c_n\}$ is a set of students. Then, we developed calculation models as for instance:

- *Calculate level of activity while resolving a task*: given a task to read elements and respond to tests $I \subseteq M$; there is a function $levAct(S_{\{c,M\}})$ that calculates the

level of activity ac_c whilst resolving the task; for instance, a calculation of time between groups of events; there is a function $avgAct(C) \rightarrow \alpha$ that calculates the average level of activity of the students in C. The function $act(c, I)$ classifies level of activity as: *slow activity* if $ac_c \leq \alpha * (1 - T_{ac})$, *normal activity* if $\alpha * (1 + T_{ac}) > ac_c > \alpha * (1 - T_{ac})$, and *high activity* if $ac_c \geq \alpha * (1 + T_{ac})$, where T_{ac} is a threshold (*e.g.* $T_{ac} = 0.2$ in our experiments).
- *Calculate level of attention while resolving a task*: given a task to read elements and respond to tests $I \subseteq M$; there is a function $levAtt(S_{\{c,M\}})$ that calculates the level of attention at_c whilst resolving the task; for instance, it takes in consideration the time between actions, time switching in and out the application (*i.e.* distractions by other applications), and others; there is a function $avgAtt(C) \rightarrow \beta$ that calculates the average level of attention of the students in C. The function $att(c, I)$ classifies level of activity as: *inattentive* if $at_c \leq \beta * (1 - T_{at})$, *attentive* if $\beta * (1 + T_{at}) > at_c > \beta * (1 - T_{at})$, and *highly attentive* if $at_c \geq \beta * (1 + T_{at})$, where T_{at} is a threshold (*e.g.* $T_{at} = 0.5$ in our experiments).
- *Calculate performance resolving a task*: given a task to read elements and respond to tests $I \subseteq M$; there is a set $E(M, I) = \{e_1, ..., e_n\}$ of optimal sequence of events to execute the instruction; there is a function $distOpt(S_{\{c,M\}}, E(I))$ that calculates the inverse of the distance pf_c between the sequence executed by the student and what would be the optimal sequence; there is a function $avgDist(C) \rightarrow \delta$ that calculates the average performance of the students in C. The function $perf(c, I)$ classifies performance as: *low performance* if $pf_c \leq \delta * (1 - T_{pf})$, *normal performance* if $\delta * (1 + T_{pf}) > pf_c > \delta * (1 - T_{pf})$, and *high performance* if $pf_c \geq \delta * (1 + T_{pf})$, where T_{pf} is a threshold (*e.g.* $T_{pf} = 0.2$ in our experiments).

Finally, there is a method to *Calculate performance resolving tests* based on the number of right answers provided to the tests $\{t1, \ldots, t_n\} \subset I$. We can then implement experiments to collect data and apply these methods in order to classify individual and group behaviour in learning environment as demonstrated below.

3.1 Experiment

In this experiment we focused on the detection of Attention Deficit Hyperactivity Disorder (ADHD) and analyse their impact in education performance. Our hypothesise is that depending on the students' behaviour it is possible to classify their profiles as ADHD inattentive, ADHD hyperactive, or normal behaviour and then compare the results from observations based on surveys conduced with these students.

We implemented a subset of the Smarter Classroom – *i.e.* tablet computers with the player application and digital education material – in a controlled environment containing students with diverse profiles[1]. The teacher delivers the class explaining in detail the whole digital education material M. Next, the teacher requests the students to execute a set of tasks to find the elements of $I \subset M$. The students execute these activities, generating logs $S_{s,M}$. Table 1 presents example results.

[1] ADHD detection: as there is no final diagnosis for ADHD level, the students have been individually evaluated based on their self-classification and behaviour.

Table 1. Example of Test Results

	Low Activity	Normal Activity	High Activity
Inattentive	Task Low / Exam Low	Task Medium / Exam Low	Task Low / Exam Low
Attentive		Task Medium / Exam Medium	Task High / Exam Medium
Highly Attentive		Task High / Exam High	Task High / Exam High

From the results, we notice that students classified as *inattentive* whilst utilising the education material attain lower performance for both task execution and exams. We concluded that the students with *low activity* in this group present the characteristics of ADHD inattentive, whilst the ones with *high activity* tend towards ADHD hyperactive – however, we grant that this observation is not conclusive and may not be always the case. During the survey, the students with known ADHD inattentive condition reported difficulty to: pay attention to the class, understand what is being discussed in a given moment, and keep attention whilst the tablet computing offers other distractions (*i.e.* applications other than the content player). On the other hand, the students with known ADHD hyperactive condition reported that they need to feel in control of the tablet computing and player application, so they spent considerable amount of time playing with the configurations. Some reported problems with the application (most likely due to misconfiguration), which let them feel impatient and disappointed with the technology.

Conversely, students classified as *attentive* and *highly attentive* attain best performance in both metrics. We cannot conclude that high activity in manipulating the education content necessarily reflects ADHD conditions for these groups. During the survey, the normal students (*i.e.* the ones whose ADHD condition is not detected) reported that: “it was easy to use the player application and the interface is friendly”. Some of the *highly attentive* users complained that other students were taking too long to complete the tasks, delaying their performance in class.

This experiment demonstrate the feasibility and potential of the technology. It is missing now more Analytic modes able to computer different performance indicators and apply the technology in diverse and larger environment to validate the results.

4 Conclusions

We presented our research in creating a interface to capture human signals in learning environment, integrated to innovative analytic models to extract meaning from this data. This development leads to alternative methods to classify and understand the impact of individual and social behaviour in the learning environments. We acknowledge the legislative, ethical, and organizational issues related to the field implementation of this proposal. However, so far we are working on proving the concept and applicability of the solutions. In further stages we will discuss the practices for field implementation.

We implement a proof-of-concept experiment to detect variations of attention deficit hyperactivity disorder (ADHD) based on level of attentiveness, activity and task performance. We could successfully detect the human signals involved in this situation and related to performance and activity whilst resolving education tasks. This experiment demonstrates the feasibility and potential of applying this technology in the field.

This development advances the state-of-the-art by introducing a method to analyse education performance based on patterns in human signals. We are building upon the solutions and case scenarios in the *IBM Smarter Education* program [6], which envisages the use of analytics to understand the learning environment. We aim to contribute to this program with a layer of understanding about individual and group behaviour and its impact on education performance.

Future work will provide extended analytic methods, implement larger test scenarios, and create recommendation modules and visualisations to facilitate decision making. In the long term, we aim to integrate these modules in a composed solution.

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