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Modelling Physical Activity Behaviour Changes for Personalised Feedback in a Health Education Application

Claudio DIAZ [a*], Olivier GALY[b] & Corinne CAILLAUD[c] & Kalina YACEF[a]
[a] *School of Computer Science, The University of Sydney, Australia*
[b] *Interdisciplinary Laboratory for Research in Education, University of New Caledonia, New Caledonia*
[c] *Discipline of Biomedical Informatics and Digital Health, Charles Perkins Centre, School of Medical Sciences, Faculty of Medicine and Health, The University of Sydney, Australia*
*cdia0348@uni.sydney.edu.au

Abstract:
Open-ended domains, where the focus is not about learning specific expert movements but about adopting healthy physical activity behaviours, require the use of unsupervised algorithms and artificial intelligence in education techniques for modelling evolving patterns from physical activity sensor data to enable feedback and personalisation. We present a suite of unsupervised window-based algorithms that detect physical activity changes aligned with learning objectives from accelerometer data. These are translated into learner model attributes and used to generate timely feedback. We illustrate our method in the context of a health education program that teaches adolescents about healthy physical activity behaviours through an application connected to a wrist-worn activity tracker. We present the feedback generated by our algorithms and report on the qualitative evaluation with four experts. We conclude that the automated feedback is useful, important and timely to leverage adolescents' physical activity learning.

Keywords: Physical Activity Tracker, Behaviour Change, Health Education, Personalised Feedback, Learner Model.

1. Introduction

Artificial Intelligence in Education (AIED) systems have focused on the students' interactions with traditional computer interfaces; however, the recent availability of affordable sensors has opened opportunities to capture new interaction types in physical and motor skill domains (Martinez-Maldonado et al., 2017; Santos, 2016), creating the need of novel learner modelling techniques to drive personalisation. In a traditional AIED system, feedback may be based on the knowledge and mistakes made by the student who executes some tasks using a computer. On the other hand, in physical learning systems, feedback may focus on the physical activity (PA) behaviours detected by the sensors. This means that the system needs to extract and assess relevant information from all sensor data in real-time, in addition to the more standard forms of computer-based interactions.

Our goal is to create techniques for extracting relevant PA behaviour change data from activity tracker time-series to determine whether students learn and improve their PA behaviours in the context of a health education programme dedicated to 10-12-year-old adolescents called iEngage. iEngage teaches health knowledge and skills related to PA, goal setting and self-assessment of achievements, and aims to promote participation in PA (Yacef, Caillaud, & Galy, 2018). The learning activities are delivered through an application connected to a wrist-worn activity tracker that records steps continuously throughout the programme running period. The activity tracker helps adolescents to monitor their PA towards personal step goals, and supports knowledge acquisition through experiential learning activities. The learning programme delivers evidence-based content about PA and health, complemented by practical activities and quizzes for knowledge consolidation. The activity tracker captures steps and feeds them back to the application. This information is then presented to the adolescents in the application, thus allowing them to self-assess their achievements against their individual goals. Indeed, learning is not just about how well students know the theoretical health facts, but also about how they translate this knowledge into actual PA behaviours in their daily life.

As the detected patterns will inform the feedback, it is important to capture, model and analyse patterns of PA changes in response to the health education programme. This allows determining whether new PA behaviours are observed in response to what they have learnt, whether these new behaviours are positive or negative, when they occur, and, importantly whether these new behaviours are maintained over time. These data are crucial to provide individualised feedback to the students.

The task is three-fold: (1) to detect changes in PA behaviours using the student's step data continuously recorded by the activity tracker, (2) to model and integrate them into the learner model, and (3) to update these data periodically to give timely personalised feedback. To this aim, we propose a framework and algorithms that we tested using step data and personal PA goals extracted from the e-learning platform from students who previously participated in the iEngage programme. We also validated the value of the automated feedback with experts.

2. Related Work

The emerging use of sensors to support PA and psycho-motor learning has led to the development of specific data analysis techniques for tracking physical behaviour patterns, modelling the learners' behaviour, and providing personalised feedback, for instance, for dance learning (Dias Pereira dos Santos, Yacef, & Martinez-Maldonado, 2017), Aikido training (Santos, 2015), and healthcare training (Echeverria, Martinez-Maldonado, Power, Hayes, & Shum, 2018).

On the other hand, learning about healthy PA behaviours does not involve learning prescribed postures or movements patterns, but achieving an overall goal represented by the recommended PA level (Organization et al., 2020). Moreover, PA changes are specific to each learner and are influenced by their fitness levels and daily schedule. Importantly, PA does not follow a particular pattern, occurs at various times of the day, with various characteristics of frequency, speed, duration and intensity. This implies using unsupervised techniques to capture PA changes during the intervention programme instead of specific activity recognition supervised techniques.

Various unsupervised techniques exist for detecting PA behaviour changes in cohorts or in individuals after an intervention (Lee, Yu, McDowell, Leung, & Lam, 2013; Dobbins & Rawassizadeh, 2015; Diaz, Galy, Caillaud, & Yacef, 2020). However, these methods are not suitable for monitoring PA behaviour changes in real-time. To provide feedback during a health education programme or intervention, live streaming data need to be collected and analysed using window-based techniques. For instance, (Dawadi, Cook, & Schmitter-Edgecombe, 2016) used semi-supervised algorithms to detect PA changes in behavioural routines from smart home sensors data during functional health assessments. Further expanding this work, (Sprint, Cook, & Schmitter-Edgecombe, 2016) created an unsupervised PA change detection framework to track behaviour changes from wearable sensor data. Our work extends these ideas by capturing the characteristics of the students' PA behaviour changes that consolidate their knowledge acquisition.

3. A Learner Model for iEngage

A learner model for physical learning environments needs to include knowledge-specific attributes (i.e. what the student knows) and PA behaviour-specific attributes (i.e. what the student actually does). In iEngage, the knowledge-specific attributes rely on the interactions with the application (quizzes, answers, and set goals), while the PA behaviour-specific attributes are constructed from the data collected by the activity tracker continuously worn by the student.

Using the PA data from the activity trackers and the knowledge-specific data from the e-learning application, we generated learning model attributes using unsupervised algorithms based on rolling window procedures. Then, we used these attributes to produce personalised summative and formative feedback content. Our method is illustrated in Figure 1.

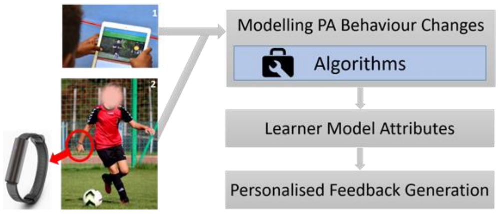

Figure 1. Schematic illustration of the method. Quizzes, answers, and goals are captured by the application (top-left photograph), and real-life PA by the wrist activity tracker (bottom-left photograph). These data are processed by algorithms and stored in the learner model as attributes to generate personalised feedback.

3.1 Algorithms for Modelling PA Behaviour Changes

We built four unsupervised algorithms to detect PA behaviour changes from step data. Detecting PA behaviour changes requires comparing present and past behaviours to identify significant differences. As PA behaviours are individual and dynamic, the algorithms use moving time windows that iteratively goes through time frames of each student's PA behaviour and analyses the presence of changes and their nature.

Difference Scanner (DS): Detects whether a student performed an hourly PA behaviour change by comparing it with the cohort's hourly PA behaviour (baseline). Using the hourly steps, it indicates when students do less PA than their peers. Specifically, the student's number of steps per hour is compared with the cohort's median number of steps per hour. This allows identifying the hours when the student does fewer steps than the cohort. The algorithm returns a data frame with two vectors: the day and the time when the difference is detected.

Rolling Window Linear Regression (RWLR): Detects recent daily PA behaviour changes. Using the number of steps per day, the algorithm measures the student's PA trend during the previous days. Specifically, it uses a 3-day window to scan the students' time series of daily steps, and calculates iteratively the linear regression for each rolling window. It returns a data frame with two vectors: the day where the window is located and the resulting linear regression coefficients.

Window-Based Interquartile Range (WBIQR): Detects recent hourly PA behaviour changes. Using the hourly steps, this algorithm labels the student's latest significant PA differences. Specifically, a time window rolls through the number of steps and time spent doing moderate to vigorous PA (MVPA) per hour. For each rolling window, the algorithm calculates the mean step number and MVPA per hour. Then, it subtracts the present-day hourly steps and MVPA from the hourly mean step number and MVPA of the windows, to generate the hourly differences of step number and MVPA. These differences are boxplotted and the IQR limits are used to detect outliers that are labelled as significant behaviour changes. It returns a data frame with eleven vectors: the date and time when behaviour changes were detected, the mean hourly step number and MVPA, the difference between the detected behaviour changes and the hourly mean step number and MVPA, the upper and lower IQR limits, and the length of the rolling window used.

Multi-Shifted Window-Based IQR (MSWBIQR): Detects PA behaviour changes that are sustained over time. Using the previously detected hourly behaviour changes, it labels as habits the changes that are repeated consecutively. Briefly, it scans the upper and lower limits of the previously detected behaviour changes from the WBIQR algorithm through the time series of the hourly step difference. If the hourly steps difference is outside the limits of the previously detected behaviours, then the behaviour change is sustained. It returns a data frame with three vectors: the sustained behaviour change date, time, and the number of days of uninterrupted behaviour change.

3.2 Learner Model Attributes

The main topics of iEngage were related to the learning model attributes to capture knowledge and specific patterns of PA behaviour. These attributes use outputs from the algorithms described in the previous section. Figure 2 lists the attributes and maps them to the iEngage topics and to the algorithms.

ID	Attribute	Attribute Description	iEngage Topic	Algorithm Used
1	Step Goals Achieved	Number of days when the step sum ≥ daily step goal	Recommended Physical Activity	DS
2	MVPA Goals Achieved	Number of days when the sum of minutes spent in MVPA per day > daily MVPA goal	Recommended Physical Activity	DS
3	Step Change	Indicates whether the daily number of steps has increased since the previous module	Be Physically Active	DS
4	Step Trend	Trend ($\beta1$) of the step number	Be Physically Active	RWLR
5	Positive Step Behaviour Changes	Number of days in which positive step behaviour changes are detected	Healthy and Sedentary Behaviours	WBIQR
6	Negative Step Behaviour Changes	Number of days in which negative step behaviour changes are detected	Healthy and Sedentary Behaviours	WBIQR
7	Positive Behaviours, Step Increase	Difference between the step number in positive steps behaviour changes and the mean step number	Healthy and Sedentary Behaviours	WBIQR
8	Negative Behaviours, Step Loss	Difference between the step number in negative step behaviour changes and the mean step number	Healthy and Sedentary Behaviours	WBIQR
9	Daily MVPA Change	Indicates whether the daily minutes spent in MVPA has increased since the previous module	PA Intensity Levels	DS
10	Daily MVPA Trend	Trend ($\beta 1$) of time spent in MVPA	PA Intensity Levels	RWLR
11	Positive MVPA Behaviour Changes	Number of days in which positive MVPA behaviour changes are detected	PA Intensity Levels	WBIQR
12	Negative MVPA Behaviour Changes	Number of days in which negative MVPA behaviour changes are detected	PA Intensity Levels	WBIQR
13	Positive Behaviours, MVPA Increase	Difference between the minutes spent in MVPA during positive MVPA behaviour changes and the mean minutes spent in MVPA	PA Intensity Levels	WBIQR
14	Negative Behaviours, MVPA Loss	Difference between the minutes spent in MVPA during negative MVPA behaviour changes and the mean minutes spent in MVPA	PA Intensity Levels	WBIQR
15	Longest Positive Habit	Positive step behaviour change that has been maintained for the highest number of days	Healthy and Sedentary Behaviours	MSWBIQR
16	Opportunity to Increase Steps	Day of maximum difference in step number between the student and the cohort	Recommended Physical Activity	DS
17	Follow-up	Number of days the adolescent did more steps than recommended (Attribute ID 16)	Recommended Physical Activity	DS

Figure 2. Map of the attributes to the iEngage topics and the algorithms used to calculate them.

3.3 Personalised Feedback Generation

We used the learner model attributes to generate timely personalised feedback to support the students' learning, motivation, and healthy PA behaviour changes. The feedback is generated by a combination of feedback types which are triggered by specific attribute values. Figure 3 show the list of feedback types and a sample of the rules used to trigger the feedback.

3.4 Illustration

To illustrate the personalised feedback each student receives, we sampled data from a real participant in a previous iEngage intervention (Yacef, Caillaud, & Galy, 2018) to generate the feedback received on a particular day. The values of each learner model attribute were calculated by our algorithms using the sampled data to trigger the feedback rules and to build the personalised feedback. This is presented to the participant as a narrative in an educational, constructive and adolescent-friendly way (Figure 4).

ID	Feedback types
A	Congratulate and encourage steps
B	Find positive changes to reinforce steps
C	Congratulate for steps goal
D	Find positive steps trends and reinforce them
E	Find positive step behaviours to reinforce them
F	Congratulate for achieving a positive habit
G	Promote following opportunity suggestions
H	Suggest opportunities for more PA during the day
I	Find negative behaviours to fix
J	Congratulate and encourage MVPA
K	Find positive changes to reinforce MVPA
L	Congratulate for MVPA goal
M	Find positive MVPA trends and reinforce them
N	Find positive behaviours of MVPA to reinforce them
O	Find negative behaviours to fix
P	State steps non-achievement
Q	State MVPA non-achievement

Figure 3. List of feedback types (left table) and sample of feedback trigger rules according to the combination of attributes values (right image).

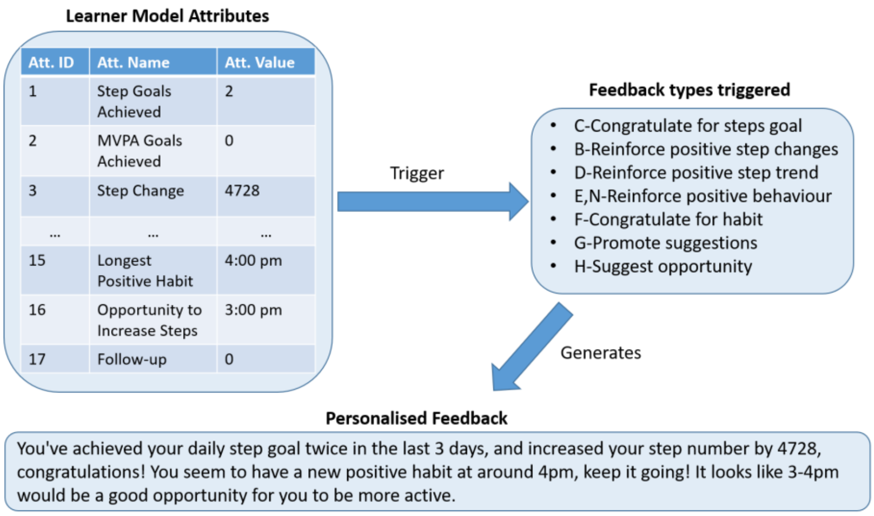

Figure 4. Illustration of the resulting personalised feedback using data of a real participant for a particular day.

4. Validation

We recruited four health sciences, exercise physiology, or physical education experts with experience working with adolescents. We asked them to evaluate via an online survey whether the automated personalised feedback was valuable (across 3 dimensions: helpful, important, and timely) for supporting adolescents who learn how to modify their PA behaviour. This online survey presented real PA data from 3 adolescents from a previous iEngage education session (Yacef, Caillaud, & Galy, 2018). The experts were asked to evaluate and comment on the feedback automatically generated by our algorithms on 3 days. This survey was approved by The University of Sydney Human Research Ethics Committee (2021/815). Each expert evaluated 44 automated feedbacks. The resultant 176 answers (4 experts * 44 feedbacks) positively evaluated the automated personalised feedbacks as helpful (mean=88%, s.d.= 11%), important (mean=85%, s.d.= 7%), and timely (mean=85%, s.d.= 8%). Experts were also asked to provide free text comments about the automated feedbacks. They found the automated feedback was good support for the students' learning process; however, they highlighted the importance of using an adolescent-friendly language in a live scenario that would need to be tailored depending on the health intervention population demographics. They also suggested students should be incorporated into the feedback loop to increase their motivation and propose more relevant actions. The study shows that valuable personalised formative feedback can be automatically generated using a combination of knowledge-specific attributes mapped with the health education application, and PA behaviour-specific attributes extracted from the activity tracker.

5. Conclusion

We addressed the problem of adding the PA accelerometer time series data into a learner model for a health education system by providing algorithms that (1) detect PA behaviour changes relevant for knowledge acquisition by students, (2) build relevant learner model attributes, and (3) provide timely personalised feedback. Window-based algorithms provide an effective way to monitor individual's PA behaviour changes over time through relevant learning-related PA behaviour attributes mapped to the learning contents. Although the actual feedback was not implemented live in our system, we show what type of feedback can be generated using these algorithms and real data from a digital health education programme that teaches health knowledge and skills to promote PA behaviour change in adolescents. Health education experts appraised that the personalised feedbacks generated by our algorithms were useful, important, and timely, indicating it is valuable for health promotion and PA behaviour change.

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