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Detection and Evaluation of Emotions in Massive Open Online Courses

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Abstract: Massive Open Online Courses (MOOCs) have grown up to the point of becoming a new learning scenario for the support of large amounts of students. Among current research efforts related to MOOCs, some are studying the application of well-known characteristics and technologies. An example of these characteristics is adaptation, in order to personalize the MOOC experience to the learner's skills, objectives and profile. Several educational adaptive systems have emphasized the advantages of including affective information in the learner profile. Our hypothesis, based on theoretical models for the appraisal of emotions, is that we can infer the learner's emotions by analysing their actions with tools in the MOOC platform. We propose four models, each to detect an emotion known to correlate with learning gains and they have been implemented in the Khan Academy Platform. This article presents the four models proposed, the pedagogical theories supporting them, their implementation and the result of a first user study.

Keywords: MOOC, affective computing, emotion detection, user modelling, learning analytics
Categories: J.4, L.2.2, L.3.6

1 Introduction

The field of educational technology has been disrupted by the emergence of Massive Open Online Courses (MOOCs) [Rodriguez, 2012]. On one hand, students are continuously enrolling in order to increment their knowledge about certain topics. This high level of demand is being compensated by educational institutions and professors that are producing and delivering more courses, either because of the

uncertainty of MOOCs impact in society or for altruism [Hew and Cheung, 2014]. In a similar way, new MOOC platforms are being launched, and those that were already established are gaining visibility at accelerated pase (e.g. Coursera[1], edX[2], FUN[3], FutureLearn[4], Miríada X[5]).

The high expectation created by the appearance of MOOCs has provoked a high-paced evolution of the pedagogical and technical approaches in order to improve their effectiveness. One of the lines of research with this goal is to leverage the knowledge gained from adaptive learning [Sonwalkar, 2013]. Educational tools like intelligent tutoring systems and recommender systems have demonstrated the benefits of personalizing the educational resources and instructional design to the profile of the learner. The application of adaptation becomes more evident when participants in a MOOC can be categorized according to their engagement [Kizilcec et al., 2013]. For instance, some researchers are also proposing the generation of personalized action plans within MOOC platforms in order to increase the learners' engagement [Nawrot and Doucet, 2014].

In an adaptive educational system, the learner profile can include information like current learning skills, learning style, learning goals and accessibility needs. Along with these characteristics, students' emotions can enrich the contextual information available in the adaptive system [Leony et al., 2013b]. Furthermore, previous studies have shown the co-occurrence of some emotions with learning gains [Baker et al., 2010]. Thus, the inclusion of affective information in MOOCs can be used to customize the learning experience or to suggest the teaching staff to perform an intervention to improve the outcomes of the course.

The inclusion of affective information can be achieved with some level of certainty through the analysis of the actions done by students in a learning environment [Baker et al., 2010]. In this work, we present four models for the detection of emotions known to be related with learning gains (i.e., boredom, confusion, frustration, and happiness). The models are defined following a rule-based approach combined with linear regression models.

The rest of the article is organized as follows. Section 2 presents a summary of research studies treating emotions in learning processes. Section 3 describes the Khan Academy platform and the interaction being captured for this study. Afterwards, section 4 presents four models developed to infer emotions from the collected data. A description of the implementation of the models is provided in section 5. Section 6 presents the results of the analysis done over the application of the four models on a data set of 90 students. Finally, conclusions and a short discussion are presented in section 7.

[1] https://www.coursera.org
[2] https://www.edx.org
[3] http://www.france-universite-numerique.fr/moocs.html
[4] https://www.futurelearn.com
[5] https://www.miriadax.net

2 Emotions and learning

The study of emotions in educational settings has been a topic of interest in educational psychology and pedagogy [D'Mello et al., 2010; Frenzel et al., 2007; García-Peñalvo et al., 2014; Kim and Hodges, 2011; Liljedahl, 2005; Ma, 1999; Meyer and Turner, 2002; Munoz-Merino et al., 2014; Pekrun et al., 2012; Pekrun et al., 2006; Pekrun et al., 2007]. Several studies have concurred on the effect that emotions have over achievement in general [Weiner, 1985] and this has also been researched in educational settings, with a higher occurrence in mathematics education. For instance Ma has presented a meta-analysis of studies analysing the effect of anxiety on mathematical achievement [Ma, 1999].

One of the initial efforts focusing on the relationship with emotions and problem-solving tasks was to identify those emotions with higher impact on the learning process. As explained by D'Mello et al. [D'Mello et al., 2010], prevalent approaches are based on goal-appraisal theories and present a cycle in which learners work fluently when they are engaged. When a learner finds information that contradicts a misconception, the emotional state shifts from engagement to confusion. It is in this moment when the learner can either correct the initial misconception and learn new knowledge or increase the level of confusion up to a point of frustration. A prolonged state of frustration can transition into boredom which is often a sink state in which learners need an external event in order to re-enter a fluent work pace.

A specific line of research in this field consists on the detection of emotions in educational environments. One approach has been the use of sensors such as webcams, meters of skin conductivity and sensors for pressure in objects like the mouse and the chair [Arroyo et al., 2009]. Other researchers have applied techniques of natural learning processing for the inference of emotions from students conversations with a virtual assistant [D'Mello et al., 2006].

A second set of research works is related to the application of emotions in educational scenarios. In our previous work we have proposed two use cases where emotions can improve learning experiences. First, emotions can be simply communicated to the instructor or to classmates in order to provide awareness of the affective state of the class [Leony et al., 2013a]. Second, emotions can be used as part of learners' profiles in order to improve adaptive applications, such as a recommender system [Leony et al., 2013b]. Calvo and D'Mello provide a complete review of the state of the art about affective computing, which provides a classification of the approaches found in the literature [Calvo and D'Mello, 2010].

3 Khan Academy Platform

Khan Academy was one of the first systems to provide a set of educational resources similar to those included in a MOOC [Ruipérez-Valiente et al., 2014]. There are some differences in the pedagogical approach followed in Khan Academy because of the lack of the concept of a course. Learners cannot enrol in a course to follow a specific sequence of activities, and it is not possible to create a community around each topic that could encourage the creation of a learning community. However, two elements

that are used in this system in a similar way than in MOOCs: videos and exercises that provide immediate feedback.

The Khan Academy platform, which was previously available as open source under the MIT license, presents educational content in video format hosted in YouTube. Following the approach seen in MOOCs, the videos tend to be short and they are assigned to a specific topic to be learned. The platform keeps track of the videos seen by the student in order to suggest the ones to watch next.

Another element common in both MOOC platforms and the Khan Academy platform are exercises. These consist of multiple-choice questions about the concepts explained in the videos. The exercise can include mathematical expressions that improve the readability of the question posed. If the learner is not completely sure about the answer to the question, the tool includes the option to provide hints. A screen capture of an algebra exercise is shown at [Fig. 1] as an example of the exercise element.

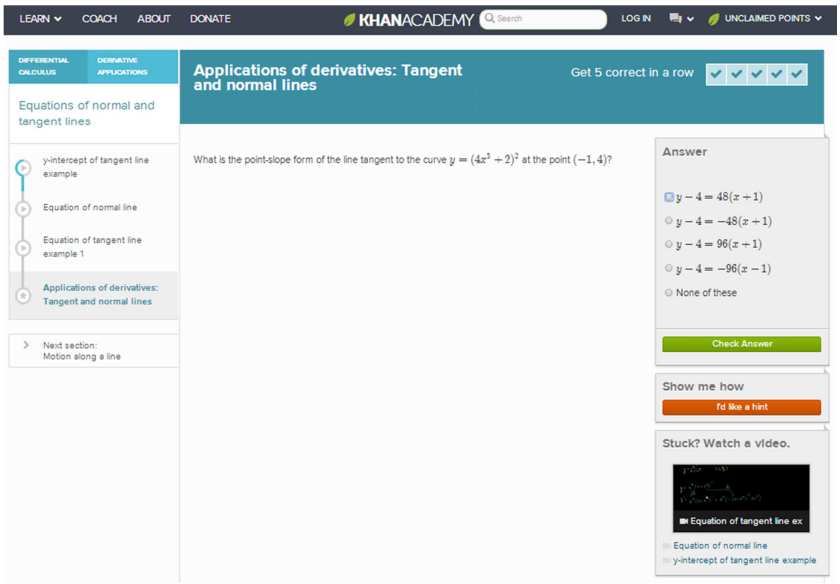

Figure 1: Screen capture of an exercise interface in the Khan Academy Platform

In addition, the Khan Academy platform provides mechanisms for gamification which are not common in other platforms. For instance, the platform attributes badges to a learner that has achieved of a specific goal, such as watching a given number of videos or answering some exercises correctly.

4 Models to Detect Emotions

Using the information available in the Khan Academy platform, we have defined four models for detecting emotions that present a correlation with learning gains of students. As shown by Baker et al. in [Baker et al., 2010], the observation of

confusion and engagement has been proven to correlate positively with learning gains, while boredom and frustration present a negative correlation.

For all of the emotions, we have selected only those events occurring during the last hour. This decision relies on the fact that more recent events tend to affect in a higher level the emotional state of a person in any context. Furthermore, those events occurring within the hour have a different weight on the current emotional state, depending on how recent they are. For instance, an event occurring one minute ago has a greater weight than an event occurring 50 minutes ago. Studies in the field have used similar criteria in order to define the duration of sessions in which the emotions are inferred [Calvo and D'Mello, 2010; Sabourin et al., 2011].

4.1 Detection of frustration

The inference of the frustration of the student (SF) is based on the learner's tries of the exercises. Those exercises are considered not to increase the frustration of the learner. On the other hand, if the last try of the student has not been correct, there is understood to be a level of frustration, with a behaviour characterized by the following equation, where A is a constant to be defined.

$$f(t) = \begin{cases} 0.7, & t < 20 \\ A * (t - 20) + 0.7, & 20 \leq t < \frac{0.3}{A} + 20 \\ 1, & t \geq \frac{0.3}{A} + 20 \end{cases} \quad (1)$$

If the student has not tried to solve the exercise, the frustration is understood to be null at the beginning and to increase with the pass of the time. The following equation is proposed to calculate the frustration generated in this case. As in the previous case, B is a constant to be defined according to the learner.

$$f(t) = \begin{cases} 0, & t < 20 \\ B * (t - 20), & 20 \leq t < \frac{1}{B} + 20 \\ 1, & t \geq \frac{1}{B} + 20 \end{cases} \quad (2)$$

As mentioned above, the frustration generated by the exercise is weighted according to its time of occurrence. The weight of the exercise is calculated with the following equation, where E represents the exercise and M the set of minutes in which the exercise occurred.

$$w(E) = \frac{1}{73810} \sum_{i}^{M} (60 - i)^2 \quad (3)$$

The same equation is used to calculate the exercise weight for the other emotions. Finally, the emotion of the student is incremented by the level generated by the exercised weighted in equation 3. This calculation is used in every emotion model given the incremental change provoked by each exercise. Thus, the equation used to update the student emotion is the following, being SE the student's emotion, EE the increment of emotion generated by the exercise, and EW the weight of the exercise.

$$\boldsymbol{SE = SE + EE * EW} \quad \textbf{(4)}$$

The result obtained is used as an index between 0 and 1 that indicates the level of frustration generated by the exercises in the platform. A diagram of the process to calculate the frustration following the equations described above is presented in [Fig. 2].

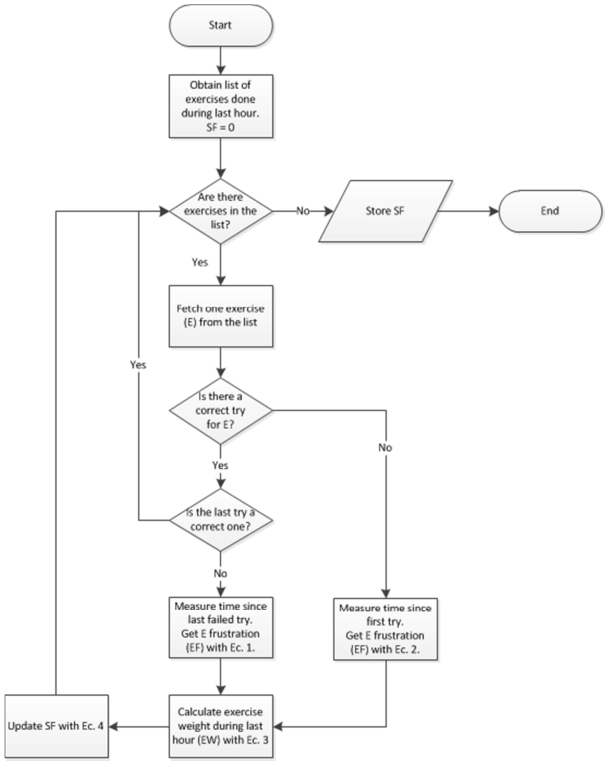

Figure 2: Flow chart of process used to detect frustration

4.2 Detection of confusion

The process to infer the emotion of confusion is similar to the one used to infer frustration. Indeed, previous works have found difficulties to define models for confusion and frustration that do not correlate between themselves [Leony et al., 2013].

In our proposal, the logic behind the definition of this model relies on one of two events. The first is the case when the student is taking a long time to solve an exercise, similar to the detection of frustration but with a different slope. The second case consists in those situations where a learner has previously solved an exercise and in a later try the response is incorrect. Thus, the concept evaluated by the exercise is not completely clear for the learner.

The surrounding steps of the model coincide with those of the frustration model: each one of the exercises done by the learner during the last hour is analyzed in order to get its individual effect on the learner confusion. If a learner has given a wrong answer to an exercise that had been solved previously, it is understood that the confusion associated to that exercise is total (coefficient of 1). The equation used to calculate the confusion generated by the exercise (EC) is the following.

$$f(t) = \begin{cases} 0, & t < 5 \\ C * (t - 5), & 5 \leq t < \frac{1}{C} + 5 \\ 1, & t \geq \frac{1}{C} + 5 \end{cases} \quad (5)$$

As in the previous cases, C is a constant assigned to each learner. It can be seen that the equation that describes the confusion in terms of elapsed time trying to solve an exercise follows the same structure that the one describing the frustration of the learner. The main change between the two models is the smaller offset on the X axis for the confusion model. The reasoning behind this decision is that the learner can be confused at a very early stage of the assigned task, while frustration is most common at a later stage, when the learner would have spent more time to try to solve the problem. The flowchart describing the process for inferring confusion is presented in [Fig. 3].

4.3 Detection of boredom

Our proposal for the inference of boredom relies on the flow theory proposed by Csikszentmihalyi [Csikszentmihalyi, 1997]. In this theory, a learner is understood to be bored when the difficulty of the challenges presented is lower than the recommended for her level of skills. On the other hand, learners whose skill levels are not enough for the problems to solve are understood to undergo through the emotion of anxiety.

The process to infer the level of boredom of the learner follows the same initial steps described in the previous two models. The list of exercises responded during the last hour are analysed individually to calculate their individual effect and calculate a weighted sum of the complete set.

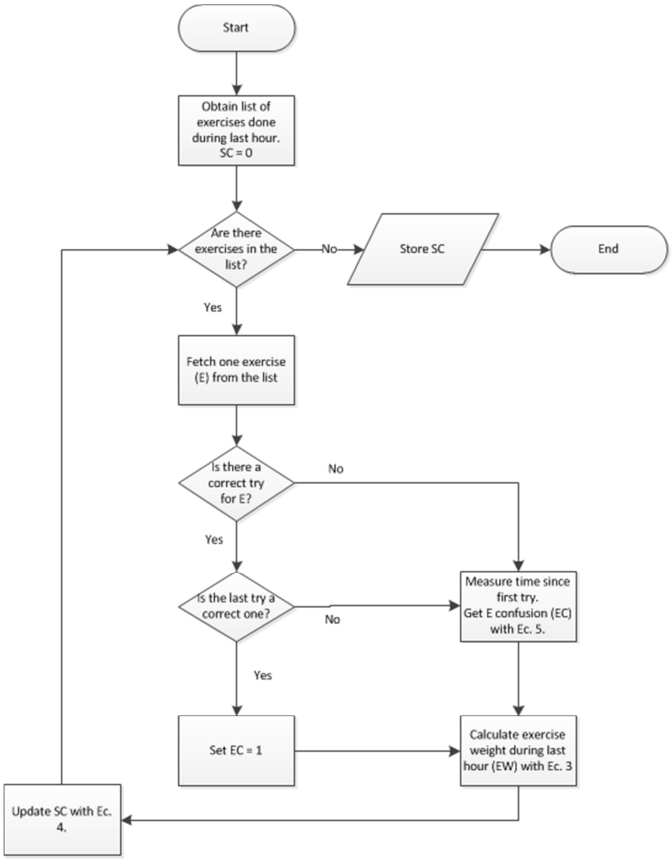

Figure 3: Diagram flow of model for the detection of confusion

The main difference in this model when compared with those for frustration and confusion is the lack of a linear function to describe the level of boredom with respect to the elapsed time. In this case the calculation has been simplified by, first, calculating the arithmetic mean and the standard deviation of the durations to solve exercises by the student. Then, we define that a problem assigned to a student is less than the expected if it is less than the mean minus one arithmetic mean. Another difference between previous models and this is that in this case an exercise is qualified to cause boredom to the student in a discrete way, this is, an exercise either cause boredom on the student or not cause it at all, while confusion and frustration were understood to be continuous functions. The diagram of the boredom model is illustrated in [Fig. 4].

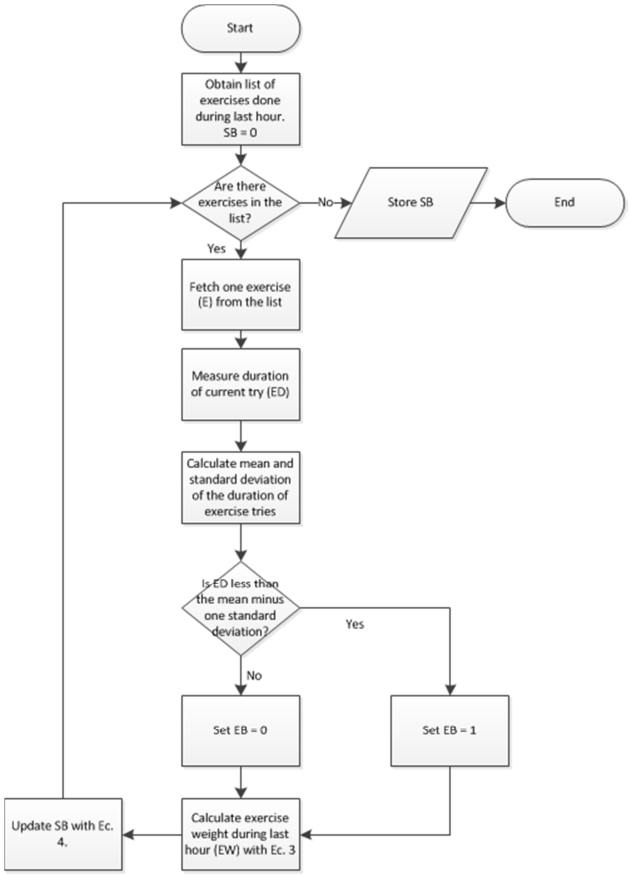

Figure 4: Flow of rules for the detection of boredom

4.4 Detection of happiness

The final model aims to infer the level of happiness that the student is experiencing as a result of the interactions with Khan Academy. Although this model maintains the idea of analysing only the events that occurred during the last hour, it also incorporates the analysis of gamification elements because of their direct relation with the happiness of the student. Specifically, we take into account the badges obtained by the learner because of solving each exercise. This hypothesis is based on Roseman's theory of discrete emotions [Roseman et al., 1990] which states that an individual experiences joy when a rewarding event is certain to happen due to a circumstance.

As a point of reference, if the work done to solve the exercise does not provide a badge to the student, the happiness generated by that specific exercise is understood to be none. This model also includes the analysis of the emotion with respect to the time that the student has taken to solve the problem. Unlike the models for frustration and confusion, the level of happiness is understood to decrease with time. The process for this model has been illustrated in [Fig. 5].

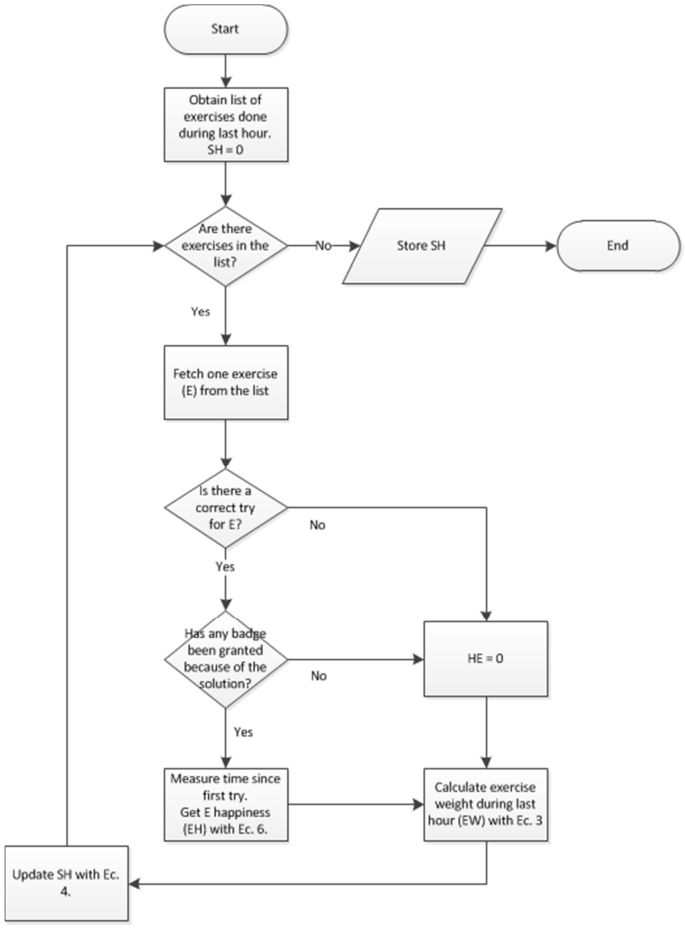

Figure 5: Flow for the detection of happiness

5 Implementation of the Models

The four models have been implemented and integrated into ALAS-KA, a learning analytics module for the Khan Academy platform [Ruipérez-Valiente et al., 2013]. This module extends the analytics capabilities provided by the platform and includes new metrics and visualizations of information obtained from the analysis of patterns of activities performed by its users.

Furthermore, the developed application can be divided in two areas: the core inference engine and the presentation layer. The implementation of the inference engine follows a modular approach, having as a basic element the code in charge of the operations frequently used in the inference of emotions. Each emotion is implemented from this starting point. Thus, the implementation of other models for

the detection of these and other emotions can easily be performed by the reutilization of these tools.

All of the implemented models take into account the ProblemLog provided by the Khan Academy. This log includes all of the information about users' interaction with exercises and the timestamp in which they have occurred. The process in charge of the analysis was scheduled recurrently in order that data processes could be executed as frequent as possible. The main advantage presented by this log is its role of gathering all of the data related to the actions of the student within the platform. This approach facilitates the process of collecting and normalizing the information generated.

The presentation layer includes the elements needed in the paradigm of Model-View-Controller (MVC). In this scenario, the view is a set of HTML templates that create a complete web page by using the data provided by the controllers. The final visualization presents a combo box to select the student whose emotions wanted to be inferred, and a table with the information of emotion changes in a timeline. Figure Fig. 7 presents a capture of the implementation of the model of frustration, presenting both the personal levels, in red, and the class group ones, in blue.

6 Analysis of case study

In order to do a first evaluation of the models, we selected a set of learners that attended the initialization courses for the subjects of mathematics, physics and chemistry during the Summer of 2013. For each subject, we obtained the top 30 learners that had worked the most with platform exercises. Thus, some learners could repeat in the data set if their interaction with exercises was relatively high in more than one subject.

The four models described in section 4 were applied on the 90 students. Each learner's actions were fed into the implementation of each model, using time ranges of 10 minutes during the time periods of August 1st 2013 at 9:50 and August 8th 2013 at 11:10, which was a period with a high level of activity in the platform. In some cases, a learner would not interact as much as needed in order to infer his/her emotions, and was then removed from the resulting dataset. The final set consisted of 44 learners and the results of the models' application is analysed in the following subsections.

6.1 Evolution of emotions through time

The first analysis performed was the accumulated values for emotions for the whole data set of students. This analysis would give an overview of the evolution of emotions during the selected date range. The timelines for these values are shown in [Fig 6].

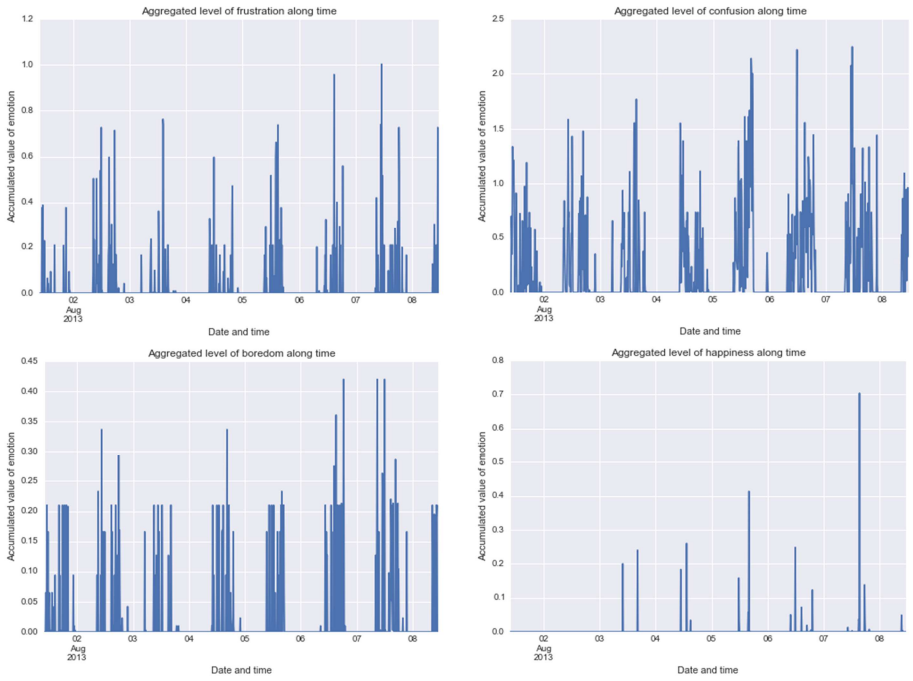

Figure 6: Timelines presenting the sum of emotion values for all students. Top to bottom and left to right: Frustration, Confusion, Boredom and Happiness

By comparing the top two graphics, it can be observed that values for frustration tend to be lower than those for confusion. This is an expected result and it coincides with previous work by D'Mello et al. where they observed transitions to frustration in extreme cases of confusion [D'Mello et al., 2014].

The accumulated boredom has also presented an expected evolution. While it is constant during most of the period, the first three days show a lower level while the last two days present higher values. The explanation for this behaviour is that students would be performing better at the end of the period and thus having skill levels higher than the needed for the exercises.

In a similar way, the accumulated happiness presents a slight increment along the analysed period. This is also foreseeable because learners are expected to be able to accumulate more badges as the course is advancing.

6.2 Accumulated emotions by hours of the day

In addition to the evolution of emotions along time, it is interesting to analyse patterns of learner's emotions fluctuations along the hours of the day. For this purpose, the values for emotions have been grouped and added by their hour of occurrence. The trend for each emotion is shown at [Fig. 7] as a line chart.

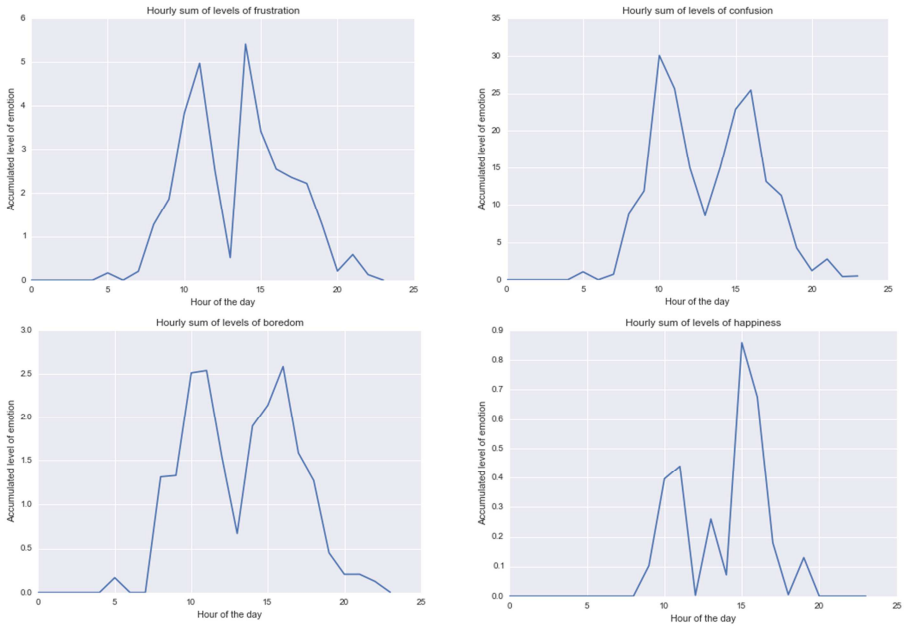

Figure 7: Accumulated values by hour of the day. From top to bottom and left to right: Frustration, Confusion, Boredom and Happiness

In this analysis, the models for frustration, confusion and boredom show a similar pattern marked by two peaks around 10:00 and 16:00. We can also observe that emotions have a null value during the night, from around 22:00 to 7:00, which is the expected behaviour. In a similar way, there is a local minimum around 13:00 for each emotion, which would correspond to a lunch period. The trends in these three emotions also follow the sequence presented by D'Mello, in which confusion can be followed by frustration which then becomes boredom.

In the case of happiness, the values are higher during early afternoon. Our hypothesis in this case is that learners are continuing their morning sessions and thus obtaining badges as result of their day work.

6.3 Correlating emotions with course metrics

As a final analysis of the emotions inferred, it was of interest to evaluate the correlation between emotion levels and five relevant indicators that can be calculated in MOOCs. Two of them are low-level: percentage of exercises solved well and time spent in exercises. The other three have been defined as follows:

- Percentage of exercises solved with proficiency: A student is considered to be proficient in a skill when the student solves correctly several similar exercises.
- Video abandonment: Percentage of videos that were started but not finished.

- Video avoidance: Percentage of videos that were not watched and whose related exercises were solved incorrectly.

The metrics listed above are understood as independent from the emotion levels because, although most of the models take into account whether an exercise has been previously solved correctly, none of them is based on percentages of exercises done correctly. In addition, the emotion models do not take into account the video usage so the models are independent from video related indicators.

The first step was to add up the calculated emotion levels for each student, thus having one value for each of the four emotions for each the 44 learners. The following process consisted on calculate the correlation index for each combination of an emotion and the selected evaluation metrics. [Table 1] presents the correlation between the sums of emotions calculated every 10 minutes with the percentage of exercises in which learners reached proficiency. Correlation coefficients higher than 0.6 are highlighted in bold.

Metric	Frustration	Confusion	Boredom	Happiness
Percentage of exercises solved well	0.490	0.440	0.309	0.151
Time spent in exercises	0.513	**0.617**	0.514	**0.713**
Percentage of exercises with proficiency	**0.607**	0.581	0.329	0.241
Video abandon	-0.296	-0.248	-0.051	-0.116
Video avoidance	-0.003	-0.029	0.113	0.065

Table 1: Correlation indexes between the sums of emotion values for each learner and their evaluation metrics

A first observation of interest is the correlation index between frustration and the percentage of exercises with proficiency. Proficiency is not considered in any model, but there is a medium level of correlation with frustration (r = 0.607) which could indicate that learners were working hard in the exercises and even failing often before to obtaining proficiency.

Another interest factor appears in the correlation between the time spent in exercises and the emotions of confusion (r = 0.617) and happiness (r = 0.713). While the model for confusion does take into account the time that students are taking in order to solve exercises, the model for happiness omits this information and this concurs with the previous paragraph, indicating that learners spending larger amounts of time in exercises have also acquired more badges.

7 Discussion and further work

The implementation and application of the four models has demonstrated the feasibility of implementing the proposed models. In addition, the initial analysis of emotion values calculated for a period of 10 days has shown some expected patterns such as increments of emotion levels as learners were interacting more with the course materials.

Most of the related work has centred the detection of emotions through the use of data mining techniques. However, the use of rules for the detection can help overcome issues such as slow start, given that at an initial moment there might not be enough data to calculate the emotion values of learners. By adding logic to the inference of each emotion, instructors can also be aware of the metrics that could have interfered in order to detect a given emotion on a learner and thus make better informed decisions.

Upcoming work will focus on the validation of the presented models by comparing with observations of learners' emotions. The actual emotion of a person may be obtained either through direct observation by an expert or through a form where students must indicate the level of each of the four emotions assessed. The latter approach is more suitable in MOOC courses given the difficulty to observe in person the massive amount of remote participants. Thus, the inferred emotions from the proposed models in this research could be compared with real state of mind of the students.

In addition, the metrics obtained in this manuscript can be used to adapt the MOOC dynamics. Thus, it would be interesting to evaluate the differences observed between a traditional adaptive MOOC and a MOOC that includes affective information as part of the learner profile. The objective of this comparison would be to obtain an insight of the affordances and disadvantages of including affective information in the adaptation process.

Another future line of research is the definition of similar models for other MOOC platforms, such as EdX. The main objective in this case is to define generic models that can be adapted to the elements provided by the platform. For instance, since most of the platforms include videos and exercises, the models presented in this article can be part of the core of such model set. Not all platforms provide means of gamification like badges to the learners, requiring the optionality to apply models that use this metric.

Acknowledgements

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