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# Towards Capturing Learners Sentiment and Context

**Jaye Clarkes-Nias**

Bowie State University  
14000 Jericho Park Road  
Bowie, MD 20715-9465  
jclarknias@gmail.com

**Oliver Bent**

IBM Research | Africa.  
Nairobi, Kenya  
oliverbent@ke.ibm.com

**Juliet Mutahi**

IBM Research | Africa.  
Nairobi, Kenya  
julimuta@ke.ibm.com

**Komminist Weldemariam**

IBM Research | Africa.  
Nairobi, Kenya  
k.weldemariam@ke.ibm.com

**Andrew Kinai**

IBM Research | Africa.  
Nairobi, Kenya  
andkinai@ke.ibm.com

**Saurabh Srivastava**

IBM Research | India  
New Dehli, India  
saurabhsrivastava@in.ibm.com

**Abstract**

We report on the motivation and qualitative studies that examine the design of a sentiment and context collection tool in a mobile-enabled blended learning technology. The tool concept emerged from field studies with teachers and students from two primary schools in Kenya. In this paper, we discuss the background and motivation of learners sentiment and context. Next, we present the overall design of the proposed module and its prototype implementation in a blended learning environment. Detailed discussions on the algorithms underlying the tool are beyond the scope of this paper.

**Author Keywords**

Education; blended learning; context; sentiment; user interface; mobile computing.

**ACM Classification Keywords**

H.5.m [Information interfaces and presentation (e.g., HCI)]: Miscellaneous.

**Introduction**

Students learning outcomes vary based on multiple factors such as skill levels, motivation, demography, teacher affinity, etc. In significant parts of the world such as Africa, varying socio-economic, cultural,

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political, religious and social factors continue to be dominant threats to learning outcomes in most public schools.

Currently, teachers are expected to perform various activities to understand their student sentiment, context and emotion. These include monitoring attendance and behavior; intervening for poorly performing students; conducting parent counseling for multiple student groups at multiple grades and varying skill levels.

Most sentiment data collection solutions (e.g., [3, 7, 1]) explicitly collect learner's sentiment (such as happy, excited, anxious) through feedback or user input; use a gamification approach to collect learners current affective state, interpret learners behavioral indicators and assess learners cognitive context through an adaptive approach [5]; or interactive context dialogue systems to share contextual situations and sentiment, experiences and knowledge [4, 6]. From our experience and as noted in [5], explicit-based data collection (e.g. by presenting questionnaires on the screen) tends to disrupt the learners experience of flow. Moreover, while novel, none of the deployed systems designed to collect sentiment data in a blended learning model.

In this paper, we combine both implicit and explicit means of collecting learner sentiment and context. The rapid adoption of digital learning delivered through web and now on handheld devices (e.g. smart phones, tablets) allows for the collection of sentiment and context data by instrumenting user-interactions with learning resources.

In what follows, first we report on our field studies that resulted in a conceptual view of a sentiment module

within a blended learning environment. Next, we present the design and implementation of a sentiment and context data collection module. Finally, we discuss and conclude the paper.

## Motivation and Field Study

Our vision for the sentiment module was influenced by (i) extensive interactions we had with a group of students and teachers from primary schools in Kenya, and (ii) the lack of existing adaptive tool-support for collecting such data.

We conducted field studies with teachers and students from two primary schools, Nairobi, Kenya. One public school with poor school infrastructure and one private school with nationally recognized infrastructure. With the teachers, our goal was to study how they identify a student struggling (*at-risk*) with sentiment/context and the perceived impact of this aspect on their students learning outcomes. With students, we experimented how they can express their sentiment with a given context using visual representations.

A key observation we made in the course of our discussions with teachers was all the teachers agreed that the sentiment and context of a student is one of the most important factors that could impede their learning progress. Upon discussion of the factors determining a student is at risk; the teachers indicated that academic performance is not the highest indicator of risk. In their experience, students from their communities may not be academically inclined but may still be successful in life due to effort. The biggest challenge for the teachers however is, how to identify the issue as early as possible, and how and when it has started. Currently, the only time they notice

**Table 1:** Sample sentiment scores.

Sentiment	Very -ve (-2)	-ve (-1)	Neutral (0)	+ve (1)	Very +ve (2)	# Pupil	Results (rounded)
Confused	0	7	0	0	0	7	-1
Excited	0	0	0	0	8	8	2
Smart	0	0	0	4	6	10	2
Great	0	0	0	1	6	7	2
Frustrated	2	6	1	0	0	9	-1
Hungry	2	5	3	0	0	10	-1

sentimental or contextual problems is either the student performance drops significantly or he or she showed some degree of behavioral changes.

With the students, we studied the interpretation of sentiment to create a broader classification based on semantic orientation on a 5-point scale. To assess how locally relevant the sentiments are we translated the English meaning of each sentiments to their Swahili (the national language of Kenya) counterpart.

Thirty-three (33) pupils from public primary school participated in this workshop. We further divided them into 4 groups, where each group was given a subset of the sentiment list (36 in total) and asked them to give polarity values on scale 1 to 5.

Table 1 shows sample sentiment scoring results from the student workshop. The sentiment score is calculated for each pupil based on a weighted average. In addition to the polarity value given to each sentiment, it also has an associated image and weighted sentiment value that is assigned.

A key observation we made in the course of this workshop with pupils was some sentiments (like scared, alone, shocked and sleepy) often considered

negative mood were ranked *neutral* by the majority of the pupils. We even have had one student who considered *alone* as the highest possible positive sentiment. All in all, 83% of the ranks as compared to our expectation. However, different results were found when the pupils were given the same sentiments in Swahili (Table 2), with 98% close to what we initially expected.

**Table 2:** Comparison between English and Swahili sentiment weights.

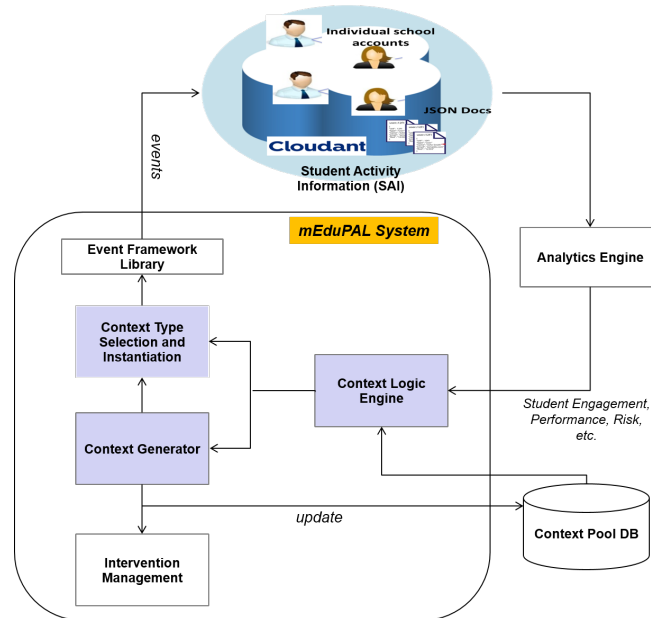
Sentiment (English)	Weight	Sentiment (Swahili)	Weight
Alone	0	Peke yangu	0
Confused	-1	Changanikiwa	0
Good	1	Vizuri	1
Happy	1	Furaha	2
Loved	2	Pendo	2
Sad	-1	Huzuni	-1
Scared	0	Uoga	-1
Sleepy	0	Uzingizi	0

The findings provided great insights to our team on how we should approach the development of a dynamic sentiment and context capturing system in a blended learning environment. Most importantly, it convinced us of the need to rigorously track student sentiment and

context along with performance and engagement factors to generate a student's holistic profile.

## Design and Implementation

As mentioned in the previous section, discussions with teachers resulted in the requirement to identify the contextual factors that can affect the learning performance of students beyond academic constraints.



**Figure 1:** Simplified view of the sentiment module architecture.

Figure 1 shows an overview of the sentiment module architecture designed with this requirement. The *Context Logic Engine* interprets two levels of explicit and implicit sentiment from the output of the *Analytics*

*Engine*, by matching to known contexts contained in the *Context Pool DB*. The *Analytics Engine* contains a number of analytics models to describe the sentiment, engagement, performance of the student. The *Context Type Selection and Instantiation* considers which context (e.g., classroom, outside classroom or interactive context) and renders the appropriate questions on the sentiment dialog interface within the blended learning environment (i.e. mEduPAL system).

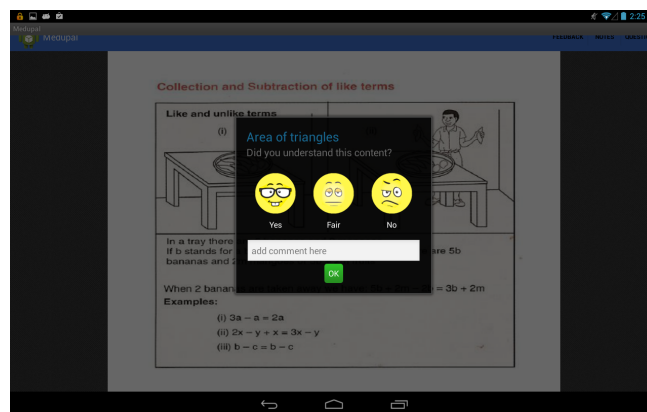
The *context generator* module draws deeper inferences on what caused a particular sentiment (e.g. if a student repeatedly indicates that “I feel sick”, the module may make use of external data sources such as demographics, available in the student longitudinal record) in order to further explore and reason about the sentiment and content of the student.

The sentiment module is designed to capture three forms of sentiment: *generic*, *content-centric* and *poll-based* sentiments.

The *generic sentiment* is meant to allow students to express their general feeling (e.g., annoyed, bored, confused, excited, happy, sad). Depending on their assessment how they feel, second level context questions will be instantiated through feedback from the *Analytics Engine*. For example “How are you feeling today?” is presented as an opportunity for a student to update their status. The response might be “confused”, the *Context Logic Engine* would then determine if further questioning based on the current context may better describe this status, e.g. “Tell me more about the source of your feelings?”.

The *content-centric* sentiment is captured in relation to engagement which is computed based on user

interactions with content on the mobile device. Upon completion of a learning activity (reading, performing a quiz, watching a video, etc.), based on the engagement level and/or performance results of the student (computed by the *Analytics Engine*), the student may be prompted to answer a question regarding their understanding of the topic presented (Figure 2). More specifically, the *Context Logic Engine* receives a dynamic input from the analytics engine, to then interpret. For example, the student's completion index for the content just viewed, along with past values of completion index in similar content items. This information is used to describe any change of the student's current learning context.



**Figure 2:** Example: Content-centric sentiment query interface.

Finally, the *poll-based* sentiment is specifically meant for in-classroom mode, to assess classroom engagement and learning outcomes. During classroom instruction the teacher can now instantiate a question and poll the class as each topic is covered, to address

the specific feedback they may seek on how the students are following the in class material. This can give the chance for the teacher to revise their instruction in realtime, with a more complete insight into the whole classes understanding, through combination with the inferences already made by the sentiment module.

It should be noted that the collected sentiment and context data are captured through the *Event Framework Library*, which is a customisable and extensible event generation and collection library. It automatically syncs the event data with the *Student Activity Information (SAI)* on cloud.

## Discussion and Future Work

We ran a limited pilot in a classroom composed of 18 students attending Grade 5 Mathematics and Science classes. Two lessons in Mathematics (topic “Area of Shapes”) and Science (topic “States of Matter”) were conducted. We tested the usability of the sentiment module as a component of the overall learning system.

For each lesson, students were given learning resources (contents and assessments/quizzes). The students posted their feeling/sentiment using the context interface when interacting with the learning system (generic sentiment). The engine further interacted with students to understand their context of the reported feeling/sentiment. Similarly, the sentiment engine was able to collect content-centric (Figure 2) and poll-based sentiments while the students interact with the content and the teachers sent poll questions to the classroom, respectively. All the collected data are sent to the cloud storage (i.e. Cloudant, a globally distributed database-as-a-service [2]). Using the

collected sentiments, we defined MapReduce functions on Cloudant, extracted views, generated visualizations and rendered on the teacher device along with performance and engagement visualizations.

Currently, we are in the process of launching a pilot at school using our technology. The availability of this data produces new opportunities for learning at scale in education where such data has not been available in blended learning environments. The opportunities are to create historic/longitudinal sentiment data for holistic student profiles (contained in the *Context Pool DB*), to better understand their learning styles/preferences and assist in the generation of interventions for struggling (or at-risk) students. Finally, using the data we will harden our technology platform and improve underlying algorithms based on field data.

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