Mining Social Behavior in the Classroom

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Abstract. Classrooms are very well suited for research on social interactions in the wild. Hundreds of hours of student interactions are rapidly accumulated. In this paper we analyze two months of video recordings from a fourth grade class, where the teacher and a sample of 3 students selected each day wore a mini video camera mounted on eyeglasses. The data reveals different gaze patterns between groups according to gender, subject, student grade point average, sociometric scale and time of day. The patterns that were found demonstrate the promising power of first-person video recordings for understanding social interaction in the classroom.

Keywords: Mining social behavior · Gaze patterns · Classroom practices · Video analysis · Educational process mining

1 Introduction

School plays a central role in our society. Students spend a large proportion of their time at school. In particular, the classroom is preponderant for understanding the learning process since it is where formal education takes place. Students spend thousands of hours inside the classroom every year. The classroom is therefore the natural laboratory for studying situated learning. Moreover, it is a very controlled environment that lends itself to studying and identifying recurring patterns of social interactions while learning, as well as the impact of teaching strategies.

When studying learning in the classroom, it is very important to identify patterns of social interaction between the teacher and students, as well as between students themselves [1],[5],[9],[17]. Both types of interaction have an effect on the classroom environment and on student learning. Most studies of classroom interaction are ethnographic studies that are manually recorded on paper by experienced teachers, principals or expert analysts during classroom observations. Some studies use video recordings of classes, with trained coders performing a detailed analysis of the video recording [1],[10],[11],[18]. These are third-person videos recorded with one or two cameras fixed to the wall or ceiling, or set up on tripods. As a process, analyzing the videos is labor-intensive, slow, tedious, and prone to mistakes. It is therefore not used very often. The problem with third-person videos is that they do not easily capture social interactions. It is difficult to work out who is looking at whom from these videos. Furthermore, it is

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difficult to identify the emotional state of an individual from third-person videos. In order to identify such emotions, it is ideal to have a front-on view of the subject's face. In addition to this, it is also very difficult to capture dialogue using third-person cameras [2].

Given the limitations of traditional classroom observations and third-person videos, it is important to find alternatives that facilitate the detection of social interaction patterns. Furthermore, it is also important to explore the possibility of automating the detection process. In this paper, we review our experience of using first-person videos. These are videos obtained from mini video cameras mounted on eyeglass frames. While similar to head-mounted cameras [13], they are less distracting for fourth graders. With first-person videos it is much easier to identify who is looking at whom at any given moment. Third-person videos require several cameras in order to solve complex situations involving obstacles and people hidden from view. With first-person videos, on the other hand, the problem is much easier and only requires the camera of the observer. It is also simpler with first-person videos to identify long-distance gazes towards other individuals. Such gazes are normally difficult to identify with third-person videos due to the fact that accuracy decreases as the distance increases. With first-person videos it is also much simpler to identify the main person that is interacting with the subject.

There are also other first-person methods for studying social patterns. One very powerful method is the Experience Sampling Method [8]. With this method, a beeper or smartphone periodically asks the subject to complete a mini survey on their current subjective experience and to state with whom they are interacting. This is performed several times a day for each subject and continues for several weeks. Interesting personal perspectives are obtained with this instrument. However, the method can be a major distraction for students; particularly those below sixth grade. Furthermore, although the method records important personal and social information, it does not capture fast, automatic and unconscious social interactions. These unconscious interactions can reveal very important social dynamics.

2 Gaze Patterns Between Groups

Social interaction patterns can be very complex. For example, imitation, conflict, arguments, and collaboration include sequences of complex cognitive processes that are not completely observable. In this study, we start with very basic events that are almost always present in social interactions. We start with an indirect indicator of visual attention: the gaze between subjects. According to [4], faces regulate social interaction and face recognition is part of a specific mechanism evolved ancestrally for monitoring both human and non-human animals. Face detection and identification are very low-level social interaction events. They only capture who is looking at whom. Even though these are very basic interactions, they can give us a powerful picture of the nature of social interaction in the wild; particularly in the classroom. For example, it can give us information about gaze patterns between the teacher and students or among students according to gender, subject, time of day, grade point average, etc. These low-level interactions are very important and form the building blocks of more complex interactions. The situation is similar to that of medicine, where there are basic, low-level physiological measurements such as temperature, pressure and heart beats. While the thermometer, stethoscope and sphygmomanometer may only measure basic events, they are essential for detecting high-level patterns that are typical of different diseases. Similarly, in social interaction, patterns of high-level interactions such as conflicts or team work can be guessed from low-level events. For this reason, it is highly desirable to detect and correctly identify gaze patterns.

We are interested in identifying gaze patterns and detecting possible differences between groups. For example, gaze patterns between male students, gaze patterns between female students, gaze patterns from male to female students, and gaze patterns from female to male students. These patterns provide important input for comparing the social impact of different explicit teaching strategies such as class layout, changes in seating, short quizzes, collaborative learning, and project-based teaching. They also provide information about implicit teaching practices such as gender discrimination and student segregation. By doing so, we hope to develop tools that will help measure the influence of certain teaching practices on social interaction patterns in the classroom.

a) b)

Fig. 1. a) Student wearing eyeglasses with mini video camera mounted on the frame and with the lenses taken out. After a couple of minutes they completely forgot they were wearing them. b) Classroom where the teacher and a sample of 3 students are wearing the eyeglasses.

3 Methods

In this paper, we report the low-level social interaction patterns provided by the gaze between subjects in the classroom. These are computed from first-person video recordings taken from mini video cameras mounted on eyeglass frames worn by the teacher and students. These are very cheap eyeglasses sold in consumer electronic stores for about USD 60. We adapted these slightly in order to record longer videos. The original batteries were removed and replaced with rechargeable, longer-lasting, lithium batteries so that they could be worn for the whole morning (from 08:15 am to 13:15 pm) without changing the battery. An extra 8Mb memory card was also added in order to be able to record the whole day. Additionally, as shown in fig.1 a, the lenses were removed from the eyeglasses in order to facilitate the view (the original lenses were not high quality) and also to minimize their weight. The recordings were manually downloaded at the end of each day.

The information corresponds to a fourth grade class from an elementary school in Santiago, Chile. This is a school with a student population that is qualified by the government as being low socio-economic status (SES). There are 36 students: 21 boys and 15 girls. The average age of the students was 10.5 years, with standard deviation of 214 days. All classes were taught by the same male teacher. The videos were recorded inside the classroom from September 26th, 2012, to November 27th, 2012, from 08:15 am to 15:40 pm. Lunch break was from 13:15 pm to 14:10 pm. The students' parents signed a consent agreement for their children to wear the video cameras and to record the information for the purposes of research. The subjects wore the eyeglasses for the whole school day, but only during class time. They took the eyeglasses off during breaks and lunch time, as well as to go to the bathroom. A total of 12,133 minutes of video were recorded, 2,600 coming from the teacher camera and the rest from student cameras. Every 30 seconds, a frame was sampled from the videos. The pictures that were obtained were then processed with the OpenCV software to detect the presence of faces. A total of 26,936 faces were detected. Each face was saved as an image file. Image files with faces were subsequently processed semi-automatically using the Google Picasa software in order to identify the subject in each file. Picasa identified a large proportion of faces, but many low-resolution images of faces were subsequently identified manually.

We define subject 1 as looking at subject 2 if the video frame taken at a given time interval reveals the face of subject 2. With this definition, a subject can be considered to be looking at several subjects at any given moment. In this paper, we do not look to identify the main subject of the observer's gaze. We simply count the number of faces in each screen shot. Each day, the teacher and a sample of 3 or 4 students wore the mini video cameras, as shown in fig. 1.b..

There are many more male students than female students, and only one teacher. The time that the subjects wore the eyeglasses also varies considerably from one user to another. It is therefore necessary to normalize the information. The idea is to estimate the intrinsic tendency to look at a certain group. This is defined as the proportion an observer looks at the group in the ideal case that each group comprises the same number of subjects. Two normalization algorithms were used. The first method assumes that the presence of each group is constant throughout the different sessions and days across the whole two-month period. The second normalization is a maximum likelihood estimation of the tendencies. These are parameters that have to be found by the CCCP [19] algorithm that tries to maximize the likelihood of the observed data. The likelihood function comes from a multinomial distribution. More precisely it is a Fisher's noncentral hypergeometrical distribution. The probability distribution assumes that the observations at different moments are independent. It also assumes that the probability of looking at any member of the group is the same for every member of the group. At moment n for a given observer, the probability distribution for the K groups is given as

$$X_n \sim Multinomial\left(\frac{M_{n,1}p_1}{\sum_{k=1}^{K} M_{n,k}p_k}, \frac{M_{n,2}p_2}{\sum_{k=1}^{K} M_{n,k}p_k}, \dots, \frac{M_{n,K}p_K}{\sum_{k=1}^{K} M_{n,k}p_k}\right)$$

Where $M_{n,k}$ is the number of members of the kth group at the moment n. The Maximum likelihood algorithm finds the tendencies p_k that maximizes the probability of the observed data. p_k represents the intrinsic tendency to look at members of the group k when all groups have the same size, and $M_{n,k}$ adjust the probability according to the sizes of the groups at moment n.

If there is high variation in the size of the groups over time then the estimation from both algorithms can be very different. There is some random chronic absenteeism within the school and therefore there is some variation in the classroom composition from one day to another. We used both algorithms and the results are very similar. We report the tendencies estimated with the simpler method that assumes a constant group size. Finally, to compute the tendency of a group of observers we average the tendencies of the individual observers.

In addition to the video recordings, a sociometric survey was given to the students where they had to assess the popularity of each classmate on a scale from 1 (least popular) to 7 (most popular). The students' overall grade point average (GPA) was also obtained. Additionally, three independent teachers of the school and that know the students, rated the students' upper-body strength and physical attractiveness in scale from 1(low) to 7(high) using a digital survey showing the name and two pictures of each student. The average rates were computed for each student for both features.

4 Results

All of the results obtained correspond to just one fourth grade class. Even though the videos were taken over two months and produced huge amounts of data, it is still just one class.

Since there was only one teacher, it is not possible to infer from the data any patterns that could be typical of every teacher, nor of fourth grade teachers or teachers from a particular kind of elementary school. The patterns detected with the teacher are only valid for this particular teacher. While they may be very interesting and could be very typical, they only illustrate the power of observation instruments based on first-person videos. However the student patterns that were obtained can be valid for students from other classes and schools. The big difference is that they come from 35 students; not just a single subject. There are several other important features of the data. The patterns are obtained from hundreds of hours of video recordings. This is much more data than is typically gathered for social studies. The data corresponds to several months of student behavior; not just a couple of sessions. In addition, this is not data that is gathered from surveys; they are video recordings that in principle can illustrate conscious and unconscious, as well as unintended behavior. Another important feature is that it is data in the wild. This is a big difference to the usual data obtained in laboratory conditions. Subjects can answer and behave very differently in laboratory conditions than in the classroom. The student patterns could therefore provide interesting findings that are present in typical fourth grade classrooms and are not otherwise detected.

First let us review only the data regarding the observers. There are some interesting patterns in the proportion of the recorded time that students look at other students. Male students tend to have more moments looking at others (39.4%) than female students (32.4%). Every time they look at a face, on average male students see 5.2 faces, while female students see 4.7 faces. These rates are much lower than the corresponding rate for the teacher. Every time the teacher looks at a face, he sees an average of 13.3 faces. From table 1 it can be seen that students tend to have more moments looking at other students during the first two sessions in the morning (46.9 %) than during the other two sessions (29.0%, 38.7% and 34.8%, respectively).

Table 1. Distribution of student video recordings throughout the day.

Block	Recorded time (min)	Time with face (min)	% time looking at others
08:15 to 09:45	2202	1032	46.9
10:00 to 11:30	3409	990	29.0
11:45 to 13:15	1608	623	38.7
14:10 to 15:40	2309	804	34.8

Students look at more people in math, language and technology classes (44.0%, 48.9%, 50.5%, respectively) than in the other subjects, such as computer lab (15.8%) and science (33.3%). More popular students (above average on the sociometric scale used) tend to have more moments looking at others (39.4%) than less popular students (31.9%).

Let us now review the data that includes both the observer and the observed. This is data about the subjects that the different groups of students are looking at. Remember that the tendencies defined and computed correspond to rates based on the ideal case that all of the groups were of equal size. It can be seen that the tendency for male students to look at the teacher (0.415) is higher than for female students (0.306) (Table 2). Both male and female students have the tendency to look at students of their own gender more than students of the opposite gender. Males have a tendency to look more at other males than at females (p-value is 0.01412). Females have a tendency to look more at other females than at males but it is not statistically significant (p-value is 0.05253). On the other hand, the tendency for males to look at other males is higher than the tendency for females to look at males (p-value is 0.002). Similarly, the tendency for females to look at other females is also higher than the tendency for males to look females (p-value is 0.002).

Table 2. Tendencies to look at classmates by gender.

Group	Tendency to look at male students	Tendency to look at female students	Tendency to look at the teacher
Male Students	0.346	0.239	0.415
Female students	0.266	0.428	0.306
Teacher	0.504	0.496	0

During the first four morning sessions, the tendencies for both male and female students to look at the teacher (0.453 for males and 0.355 for females) are much higher than for the remaining four sessions of the day (0.211 for males and 0.148 for females). Both differences are statistically significant, with p-values 0.006 and 0.035, respectively. Both males and females have the tendency to look at the teacher a lot more in math classes (0.463 for males and 0.621 for females) than in other classes. For females, the difference between math and language is statistically significant with p-value = 0.002. Interestingly, in art classes female students almost never look at the teacher (tendency is 0.116), instead mainly look at female classmates (tendency is 0.640). The tendency for females to look at other females is much higher in art than in language (p-value = 0.07) and math (p-value = 0.0087). This is also the case in language classes (tendency is 0.056), although they increase their tendency to look at their male classmates (tendency is 0.567). The tendency for females to look at males is higher in language than in math classes (p-value = 0.000008), and is also higher than in art classes (p-value = 0.00097).In contrast, the tendency for males to look at other males does not change much from one subject to another (all p-values are above 0.18). Similarly, the tendency for males to look at females does not differ between art and math classes, nor between math and language classes (p-values are 0.44, and 0.25, respectively).

According to grade point average (GPA), above-average students have a higher tendency to look at the teacher (0.417) than below-average students (0.324), but it is not statistically significant (p-value is 0.27). However, in math sessions (Table 3), above-average students in terms of GPA have a much higher tendency to look at the teacher (tendency is 0.593) than in other classes (e.g. 0.246 for art class), which is statistically significant with p-value = 0.004.

Table 3. Tendency to look at classmates, by academic performance (GPA) for different subjects.

Session – group	Tendency to look at high GPA students	Tendency to look at low GPA students	Tendency to look at the teacher
Art sessions – high GPA	0.473	0.281	0.246
Math sessions – high GPA	0.250	0.157	0.593
Language sessions – high GPA	0.309	0.283	0.407
Art sessions – low GPA	0.530	0.311	0.159
Math sessions – low GPA	0.298	0.241	0.461
Language sessions – low GPA	0.373	0.401	0.225

This pattern for above-average GPA students is also true for all the sessions of academic subjects (math, language, science and history). The tendency to look at the teacher is 0.474, which is higher than the tendency to look the teacher during the other sessions (tendency is 0.166). The difference is statistically significant with p-value = 0.0006. Popular students (above-average according to the sociometric scale used) also have a higher tendency to look at the teacher in math classes (tendency is 0.533) than in other classes (e.g. tendency for art is 0.242, the difference between math and art is statistically significant, with p-value =0.038). Interestingly, this teacher's tendency to look at above-average GPA students is 0.580, which is much higher than his tendency to look at the rest of the students (0.420). The same is true for his tendency to look at popular students (tendency is 0.585) than the others (tendency is 0.415).

Studies in evolutionary psychology have found interesting patterns of social interaction according to physical features in male and female adults. Upper-body strength in males and visual attractiveness in females provides better bargaining positions in conflicts and regulates emotions such as anger [15],[16]. There are also studies with a K12 student population. For example, according to [6], "the core of the self-schema is predicted, from an evolutionary perspective, to be referenced in terms of one's standing vis-à-vis peers and particularly for traits that have an evolutionary history, including physical abilities (greater importance for boys than girls), physical attractiveness (greater importance for girls than boys), social influence, and family status…the best predictor of global self-esteem from childhood to adulthood is perceived physical attractiveness [7] and not, for instances, grades in high school mathematics classes". To investigate the impact of these physical features on gaze patterns, three independent teachers subjectively scored the upper-body strength and visual attractiveness of the 36 students. By averaging these scores, an upper-body strength index and attractiveness index were computed for each student. It can be seen (Table 4) that the tendency for above-average upper-body strength students to look at classmates with above-average strength (0.574) is much higher than their tendency to look at below-average upper-body strength classmates (0.426). However p-value is only 0.093.

Table 4. Tendency to look at classmates according to upper-body strength.

Upper-body Strength	Tendency to look at students with high upper-body strength	Tendency to look at students with low upper-body strength
High	0.574	0.426
Low	0.497	0.503

The tendencies for both above- and below-average attractive students to look at attractive classmates (0.558 and 0.568) are higher than for below-average students (0.442 and 0.432, respectively), both findings are statistically significant, with p-values less than 0.001. In the case of male students, the difference in tendency is also pronounced. The tendency for male students to look at attractive female classmates is 0.537, which is higher than chance (0.5) with p-value less than 0.001. It is also much higher than their tendency to look at below-average attractive female classmates (0.463).

5 Conclusions

We have analyzed two months of first-person video recordings. Every day, the teacher and a sample of 3 students wore eyeglasses with mounted mini video cameras. By doing so, a big amount of first-person visual data was recorded. The huge data sets obtained offer unique possibilities to do reality mining [14] to find very valuable face-to-face social patterns that are very difficult to obtain by other means. The gaze patterns that are reported are very interesting. Some of them are specific to this particular teacher and classroom. Others are more general findings that help us understand what happens at the classroom level with fourth graders. First-person video analysis is an interesting social mining tool. We have seen how low-level gaze patterns inform interesting social interaction patterns in the classroom. We have explored and discovered different gaze patterns according to the time of day, subject, academic performance, social popularity, gender, and certain physical features of the students.

There are several extensions that would be very important to carry out in the near future. First, there is the need to record and analyze video data in other classrooms. The statistics obtained in this study correspond to a particular classroom. It is necessary to record interactions with other classes in order to claim general patterns that are independent of specific situations. It is crucial to test the current findings on larger populations of students and teachers. Another extension to be carried out in the future is to analyze the gaze in terms of the main face that appears on the screen capture. In this paper we have counted all of the faces that are captured at each moment. Identifying the main face and analyzing interactions with the main subject could lead to some other patterns that can complement the ones reported here. Another extension for future work is to control and measure the impact of different teaching strategies. This requires examining basic strategies like classroom layout, position of whiteboards or other materials and changes to seating strategies, to more complex strategies such as teaching a whole class or team work. Another important issue is to measure and research the synchronization of gaze interactions. What happens just after the teacher's gaze is directed at a student? Will she direct her gaze at the teacher? What happens just after a student gaze is directed at a classmate? Another extension of this work is the use of first-person videos to measure student learning in interpersonal skills. Educators [12] criticize standardized tests such as PISA, which exclude assessment of the learning of social interactions in the classroom, such as power and position, leadership, submission, and social rules. These types of learning are very important. However, they are very difficult to measure with typical standardized tests and extremely slow and laborious to do with traditional ethnographic and class observation visits. However, analysis of interactions from first-person videos opens up tremendous opportunities for measuring progress in social learning.

The first-person instrument used in this study provides a new methodology for observing classroom dynamics that could lead to the discovery of important classroom realities that are hard to detect for the naked eye. First-person video analysis can help to open the black box of classroom practices. It can also help teachers share their pedagogical capital [5].

The invention of the microscope in the 17th century caused a revolution in biology by revealing structures that could not be observed with the naked eye [3]. Similarly, the ability to record first-person videos and thereby to detect gaze patterns between groups can reveal unsuspected social patterns and significantly improve our understanding of the dynamics of classroom practices.

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