Predicting Student Seating Distribution Based on Social Affinity

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Abstract. Learning students social affinity and modeling their social networks are beneficial for instructors to design proper pedagogical strategies. Students seating distribution contains social data and can be used for analysing their social relationships. In this paper, we propose a method to automatically construct the class social network and predict the position of a student's seat in class. First, we determine the positions of each student in a classroom by utilizing the center projection principle and linear fitting algorithms. The intimate relationship between students is captured to model their social network based on Euclidean distance. Then, we learn the social affinities from the Social Affinity Map (SAM) which clusters the relative positions of surrounding students. Based on this, students' seating distribution can be predicted successfully with accuracy reaching 82.1%.

Keywords: Social network · Center projection · Seating prediction

1 Introduction

In educational environments social interaction between students plays an important role in promoting efficient learning. It means that students can effectively share information and learn from each other. Understanding how social interaction works is beneficial for instructors to design better pedagogical strategies. Therefore, a large amount of effort has been spent on collecting immense social data for students.

We believe that the distribution of seats in a class contains important social relations between students [1]. In universities, students can select their seats

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freely when in class, which is the reflection of the evolution of social relations between students. As a result, a new method to collect social data is to record students' seating distribution for each class.

In this paper, we utilize class social network to model intimate relationships between students and predict their seating positions. The framework of our study consists of two parts: constructing class social networks and predicting the average distribution of students' seats. First, we need to acquire enough social data. In data collection, the instructor takes a photo of the students at the beginning of the class, and in each class, a single image including all the students faces is captured. This image not only can extract students' social data, but also can be used for class attendance via face recognition. Then, the AdaBoost algorithm with skin-color model [2] is used to detect and recognize the students' faces in the photo taken in class. Following this, the center projection principle and linear fitting algorithms are used for locate students' position. Relationship between students can be determined by the Euclidean distance of their locations. Later, we modify the SAM [3] to build the eight neighbors around each student. In this way, the habit of how students choose companions are recorded. Finally, the prediction of the seating distribution can be obtained after a long-term accumulation of the statistics of seating distribution. The seating distribution prediction is based on the assumption that if two students are friends, their seats are close.

It is proved that both the arrangement of seats in class and the distribution of students affect the learning performance of students [4–6]. Usually the students who sit together are more aware of each others behavior. Once a student is absent for no reason, it is more efficient for the instructor to ask the student who has a good relationship with him or her, rather than the whole class.

There are two major contribution of this paper:

1. We automatically determine the positions of students based on the center projection principle and linear fitting algorithms.
2. We modify the feature descriptor to capture the adjacent seat of each student to learn the social affinities, and propose a prediction method of the seating distribution.

2 Related Work

Human social behavior has attracted significant research attentions, with many positive results being proposed [7–9]. Alahi et al. [3] proposed a descriptor named as SAM which bind people in a crowded space to learn the various social affinities. They find that pedestrians mobility is effected by their neighbors and utilize SAM to predict their destinations. Their experiments showed great improvement in performance through the use of SAM features. Hong et al. [10] proposed a group recommendation method based on social affinity and trustworthiness, with outstanding performance compared to other methods.

Social Network Analysis (SNA) can be used for investigating people's collaboration patterns [11,19]. With rapid advancement of technology, there are also many applications of social networks in education management [12,13]. For example, one can take advantage of SNA to promote student interactions that accelerate the learning process [14]. Becheru et al. [15] proposed a conceptual knowledge extraction framework to extract information from student social networks that satisfy an instructor's pedagogical needs. Halawa et al. [16] created a data model to predict student personality type and learning performance based on the Myers-Briggs Type Indicator (MBTI) theory. This model makes the learning process more personalized for students and avoids the one-size-fits-all learning model problem in the field of education.

However, these research findings are based on the virtual network environment rather than real life at school. Thus, it may lead to a contradictory conclusion. This necessitates a good method which can be easily applied to real-life classroom. The classroom's seating distribution influences the climate and students relationships with each other [17,18]. A well-considered seating distribution can improve students' behavior and learning performance. Wei [20] proposed multimedia technology which can recognize the positions and identities of the students in a classroom to solve the problem of large-scale social data collection. They also designed the in-class social networks which consists of student-to-student and student-to-teacher interactions to analyze the co-learning patterns among students. However, this method is not fully automatic in identification. The number of row and column seats in the classroom need to be manually marked. In addition, since this method is based on image stitching and alignment algorithms, some requirements must be satisfied when acquiring the data. For example, all images must be taken in the same classroom, and two images should have enough overlapping regions for stitching.

3 Social Network Construction

In this section, we aim to model students' class social networks. We achieve this by analyzing the distribution of the seats and finding intimate relationship between students. We develop a social affinity feature which captures eight neighbors around each student.

Taking into account the fact that students are greatly affected by friends when they choose their seats in class, those who sit close to a target student tend to have a close relationship with the target student. For example, we observe that there are two students sitting together twelve times among the total 26 records of attendances in a semester. Figure 1 shows the four scenes where they sit together. Upon inquiry, we learn that they are really close partners in their daily lives.

3.1 Student Localization

In order to acquire social data, the instructor needs to take photos before class, including all the students in the classroom during the whole semester. After each class, the instructor submits the photo to the attendance taking website which is developed by us. The faces in the image are automatically detected

Fig. 1. Two students with close relationship often sit together, there are four scenes shown in the image (a) (b) (c) (d).

by the website. To improve the accuracy of student identification, students are asked to login on the website with their ID to confirm their face and complete attendance as well. Then, center projection principle algorithms are utilized for student localization. First, we pick out the student who seat in the leftmost column and the rightmost column in the classroom. Second, we regard them as discrete points, and use a linear fitting algorithm for these discrete points. We obtain two linear equations with least squares method. The least square formula is as follow:

$$k = \frac{\sum xy - \frac{1}{N}\sum x \sum y}{\sum x^2 - \frac{1}{N}\left(\sum x\right)^2}, \tag{1}$$

where k denotes the slope of the linear equation, N denotes the total number of fitting points, x and y denote for the horizontal and vertical coordinates of students respectively.

Fig. 2. In this figure, the leftmost and the rightmost seats lines are marked with yellow lines. The intersection point P is the center projection point of the classroom. (Color figure online)

According to the principle of central projection, each line (we abstract each column of seats into a straight line) is extended infinitely at the same point, which is called the center projection point. The intersection point of the two straight lines is the center projection point of the classroom. The coordinates of the center projection point can be obtained from the linear equation of two arbitrary column seat lines in the two-dimensional coordinate system. In this paper, we utilize linear equations of the leftmost and the rightmost seat lines to calculate the center projection point (see Fig. 2).

We regard each column of seat in a classroom as a straight line through the center projection point, then locate the student to determine which students belong to the same column. However, since the physical stature and seating position of every student is different, the position of the students in a specific column is not precisely distributed on the same line. To address this problem, we use the angle measure evaluation method (AMEM) to judge whether students belong to the same column. Specifically, for each student, we calculate the slope of the line which goes through the central projection point and the coordinates of this student's seat. Then, we pick out the adjacent students obtained in the previous step. The angle between two lines is measured by:

$$\tan\theta = \left|\frac{(k_2 - k_1)}{(1 + k_1 \times k_2)}\right|, \tag{2}$$

where θ denotes the angle of two lines, and k_1 and k_2 are the slopes of two lines respectively. Finally, we select the students who have the minimum tangent as in the same column with a specific student.

Fig. 3. The illustration of eight neighbors around a student.

Based on the Euclidean distance between two points, we can determine students who are adjacent to each student. In general, we choose four adjacent students for each student. That is, we pick out four student whose seats are one of the four seats with the least Euclidean distance from the center students seat. The number of adjacent seats can be changed according to the number of students in the classroom.

3.2 Deskmate Matching

We classify the adjacent seats into three relations: deskmate, front-rear desk, and diagonal desk. In most situations, seats are often arranged as long rows which are close to others. In this kind of situation, the deskmate of this type of seat

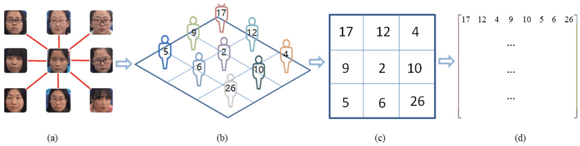

Fig. 4. Illustration of how to build a Social Affinity Map. The student in the center of the left picture is labeled as 2, around her there are eight adjacent students in sequence, namely, $17, 12, 4, 9, 10, 5, 6, 26$. These eight IDs exist in this students model as one attendance.

includes the left and right sides. In the three adjacent seat relations above, the most intimate relationship between students is the deskmate relationship. So, we need to identify all pairs of deskmates from an image.

To identify all the pairs of deskmates from a class, we need linear fitting of each column of seats. Matching deskmates can be formulated as a judgment process as:

$$f(a, b) = w \times h(a, b) + (1 - w) \times g(a, b), \tag{3}$$

where a and b denote the coordinates of the students in two adjacent columns, respectively. $h(a, b)$ denotes the Euclidean distance between points a and b. $g(a, b)$ denotes the absolute value of slope of the line through the points a and b. w denotes the coefficient of proportionality, and the value in the range (0,1). $f(a, b)$ denotes the weight used to measure whether two students are deskmates, and the larger the value is, the lower the probability of the two students to be deskmates. For each student, calculate the weight of each adjacent column, the students with the least weight are selected as their deskmates.

In this section, we use the central projection principle and linear fitting algorithms to construct students class social network. Compared to other existing methods, this method is fully automated. In addition, the method can address the issue of images taken in different classrooms; such as, the desk movement and different columns and rows in classrooms. After "student localization" and "deskmate matching" for plenty of images, the final social network of the students can be constructed to predict the seat distribution.

4 Average Seat Distribution Prediction

Students' social affinities are mostly determined by the proximity of students to each other in a class. That is why good friends usually sit together. We modify a feature descriptor SAM [7] to learn the in-class social affinities. Our model records the positions of eight neighbouring students around each one, as shown in the Fig. 3. In the direction, they are front, back, left, right, and four diagonal relations. In the example shown in Fig. 4, around the student whose ID is 2, this student's eight adjacent students in sequence are 17, 12, 4, 9, 10, 5, 6, 26. This means we build a model for each student to record the eight people sitting around for each attendance. Therefore, the model denotes as M can be calculated by:

$$M = \begin{bmatrix} C_{0,0} & C_{0,1} & \cdots & C_{0,7} \\ C_{1,0} & C_{1,1} & \cdots & C_{1,7} \\ \vdots & \vdots & \ddots & \vdots \\ C_{n,0} & C_{n,1} & \cdots & C_{n,7} \end{bmatrix}, \tag{4}$$

where $C_{i,j}$ denotes a student who is sitting at the student's next j desk in *i-th* attendance.

In Sect. 3 we obtain all the students' position data and social affinities in the classroom. Based on this foundation, students' seat distribution can be predicted. For predicting the distribution of seats, we should determine some of the students' seats first. We choose the students who have the lowest frequency of changing their seats and place them to the seat where he or she is most likely to sit. The set of placed students is denoted as A, and the proportion of students in set A is about 1/3 of the total number of students in the class. The scale of proportion needs to be adjusted appropriately when the number of students is different or the classroom is changed. Following this we extract a student whose seat is the most frequently adjacent to anyone in A according to SAM, and place him or her on their adjacent seats and add to set A. This step is repeated to get the final seat distribution result. In the process of predicting the seat distribution we utilize a greedy algorithm, i.e., each placement of students is the most appropriate choice in the current situation.

Figure 5 shows the predictive process intuitively, (a) shows the seat distribution after one third of students have been fixed. Then we place the remaining students one by one with a greedy algorithm. For example, consider the student who with the red border has the most times seating together with the student on her left. Thus, the student with the red border can be fixed as shown in Fig. 5(b). The remaining steps are similar in principle.

In order to verify the accuracy of seat distribution prediction, we need to collect a large amount of attendance data over a long period of time. We take photos in different classrooms and periods to avoid the impact of accidental data on the prediction accuracy. When evaluating the performance of the prediction of seat distribution, we leave one part of the photos as a test dataset. To simplify the distribution of students' seats in a classroom, we divide the classroom into eight areas according to the spatial locations. Figure 6 shows schematics for partitioned areas for rectangular classrooms. Through similarity comparison between the predicted results and the actual positions, we can evaluate the accuracy of the prediction. If a student's two results belong to the same area, it means that this student's seat is correctly predicted. The accuracy of the prediction is calculated as follows:

$$s = \frac{l}{D}, \tag{5}$$

where D denotes the total number of students, and l denotes the number of students whose predicted position and actual position belong to the same area.

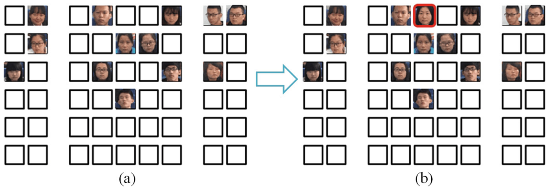

Fig. 5. Illustration of how to predict a student's seat. The squares represent seats in the classroom. (a) shows the seating distribution after a third of the students are fixed. (b) predicts the seat position of the student with red border. (Color figure online)

5 Experimental Results

We took photos of attendance for each class over a semester, and finally got 26 attendance images. These photos are split into two parts, 25 photos are used as the experimental dataset to construct the social network, while the other one photo is used as the test image to validate the prediction of seat distribution. In the classroom, students are encouraged to choose seats freely so as to observe seat distribution among students.

To evaluate the accuracy of "deskmate matching," we use the method in Sect. 3 to analyze each photo and get all pairs of deskmates. Through artificial comparisons, in this experiment there are 33 students for whom matching deskmates are correct (39 students in total), i.e., the accuracy of deskmate matching method is 84.3%.

The SAM model is filled with the student coordinate data obtained in Sect. 3, then the seat distribution of test dataset can be predicted by the method in Sect. 4. The correct number of students in this experiment of seat distribution prediction is 32 (39 students for all), so the accuracy of prediction is 82.1%.

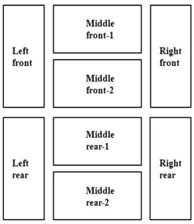

Fig. 6. Illustration of how to divide the rectangular classroom into eight areas.

In this section, we quantify the social relationship as a model and apply it for prediction of students' seat distribution. It can help instructors quickly find the proper student to inquire why his deskmate is absent, keep abreast of the absence of students and avoid accidents. In addition, the prediction results of seat distribution represent the trend of students' future choice of seats. Then, students' future learning trends can be understood, and timely guidance and help for students can be provided.

6 Conclusion

We acquired social data from attendance images with high efficiency to construct class social networks and explore the social affinities between students. A pilot study for the prediction of students' seat distribution was conducted, and the experimental results show the accuracy to be 82.1%. The representative seat distribution data will provide the data sources for studies relating to pedagogical research. We believe that with more social data, more valuable information can be extracted. In future work, we plan to extend our research on social networking. For example, the potential relevance of a student's performance considering his or her neighbouring groups is worth future investigation.

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