

# Key Student Nodes Mining in the In-Class Social Network Based on Combined Weighted GRA-TOPSIS Method

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## ABSTRACT

In this paper, a key node mining algorithm of entropy-CRITIC combined weighted GRA-TOPSIS method is proposed, which is based on the network structure features. First, the method obtained multi-dimensional data of students' identities, seating relationships, social relationships, and so on to build a database. Then, the seating similarity among students was used to construct the in-class social networks and analyze the structural characteristics of them. Finally, the CRITIC and entropy weight method was introduced for obtaining the combined weight values and the GRA-TOPSIS multi-decision fusion algorithm to mine the key student nodes that have negative impact. The experiments showed that the algorithm of this paper can evaluate students objectively based on their classroom social networks, providing technical support for process-oriented comprehensive quality education evaluation.

## KEYWORDS

Entropy-CRITIC Combined Weight, GRA-TOPSIS, Key Nodes, Process Evaluation, Structural Characteristics Analysis

## INTRODUCTION

The smart classroom provides more diversified, massive, real-time, and valuable data for educational big data in the smart teaching scene, as well as data for research of the in-class social network composed of students seats, interactive behaviors, etc. (Chen & Zhang, 2020). Studies related to in-class social networks are trying to go beyond the traditional methods of obtaining data through questionnaires and psychometric tests, which are not easily accessible and have subjective biases (Grunspan et al., 2014; Li & Stone, 2018; Van Rijsewijk et al., 2018). Wei and Yang (2012) used OpenCV and a skin

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color detector to identify students in the classroom, used linear regression to identify student seats, and constructed an in-class social network based on the co-occurrence of the corresponding students sitting in neighboring seats. Pei et al. (2018) modeled an in-class social network by capturing student photos before class using the AdaBoost algorithm for face detection and recognition, and then utilized the center projection principle and linear fitting algorithms to locate the position of students in the classroom. Beardsley et al. (2019) designed an online classroom orchestration tool, ClassMood App, to collect student data. However, the networks built by existing construction methods are mostly static networks, which cannot reflect changes in multiple areas, such as students' seats and status, for intelligent teaching process-based education evaluation.

Based on the in-class social network, many studies have found correlations between the network features and student academic achievement, motivation, and student friendships. Pulgar (2021) noted that students with high network centrality not only have higher levels of class prestige and popularity, but also have many social connections with classmates and thus enjoy the advantages of information and collaboration. Buchenroth-Martin et al. (2017) studied the interactions of students in an evolutionary biology class and used social network analysis to find that factors such as student network centrality, gender, and attendance influenced student classroom performance.

However, most of the existing network analyses are static and holistic, and there is no study of individual students' processes. At the same time, students are highly susceptible to the influence of peers around them in the classroom, and this subtle influence is often reflected in students' classroom learning status and academic performance (Raca & Dillenbourg, 2013; Raca et al., 2013). Therefore, the researchers analyze the structural characteristics of the classroom network and discover the key nodes. The results of such analysis will reshape the student learning process in terms of feedback, personalization, and probabilistic prediction, which will allow educators to understand the student learning process, improve the effectiveness of classroom instruction, and predict student learning trends.

Based on the above analyses, this paper proposes a dynamic construction method of an in-class social network for real classroom environment scenarios. The authors adopt the Entropy-CRITIC combined weighted GRA-TOPSIS (EC-GTOPSIS) algorithm based on the combination of network characteristics to rank the student nodes of the in-class social network, and comprehensively analyze the relationship and evolution trend of ranking results with student friend nomination, negative friend nomination, and academic performance. The authors then mine student nodes with negative impacts. These are defined as student nodes with poor learning effects for the students themselves in the classroom setting, and a strong negative impact on those around them. Thus, this paper provides a novel perspective for teachers to evaluate students' learning processes. It offers the following contributions:

1. Construction of an in-class social network using the dynamics of student classroom seating similarity to better reveal what underlies student seating relationships and reflect subjective trends in student seating choices.
2. Proposal of a multi-decision fusion algorithm for negative node mining within the in-class social network, which can not only select nodes with a negative impact in classroom, but also reflect the future trends of students.

The remaining parts of this paper are organized as follows: Section 2 introduces the related research work. Section 3 describes the construction method of the in-class social network. Section 4 describes the key node mining algorithm of the in-class social network based on EC-GTOPSIS. Section 5 shows and analyzes the experimental results. Section 6 concludes the paper and looks ahead.

## BACKGROUND

Recent studies using graph theory and social network analysis (SNA) methods to analyze classroom data provide the ideas and theoretical basis for our research. Putnik et al. (2016) used student interaction

data to construct networks, correlated them with students' academic performance using SNA, and found a strong positive correlation between students' centrality and academic performance. Sui and Hua (2015), using the SNA method, found that male students in the experimental class had problems with disharmony, looseness, and contradiction, and their close relationships and average grades were much poorer than those of female students. Zwolak et al. (2017) used network analysis to find that the higher the network centrality of students, the higher the probability they will persist in that field of study. Williams et al. (2019) found that students' future academic performance could be predicted by their social network centrality, and the predictions were higher than the GPA prediction methods often used.

In addition, a few studies have examined interactions among students in classroom settings. Gomes (2019) found that students' absenteeism not only has a negative impact on themselves but may also pull down the performance of others in the same educational setting. Using an intelligent seat selection and check-in system coupled with electronic campus cards, Huang et al. (2022), with the help of spatial statistical analysis, found a strong correlation between social relationships and seating distribution, with well-connected students tending to sit together, and students with close social relationships tending to sit in groups. Gao et al. (2022) used wearable physiological sensors to research how individual and group classroom seating affects students' engagement and found that students who sit together tend to have a high degree of physiological synchrony and are more likely to have similar learning engagement. Minami and Ohura (2020) used the distance between students' seats as a measure of their friendship relationships and found student groups. Dokuka et al. (2015) used a stochastic actor-oriented model (SAOM) to analyze students' social networks and found that students tend to choose classmates with similar academic achievements as their friends.

In summary, SNA has been widely used in the field of educational big data, but most of the studies are holistic. There remains a large gap in the research on individual student learning mining and its influence. Therefore, the researchers have constructed an in-class social network based on students' class seating relationships and have used a multi-decision fusion approach to tap into the significant negative nodes within the intra-class social network. This allows teachers to keep abreast of social relationships among students, to keep track of students with potentially high negative impact, and to provide timely interventions for individual students, thus optimizing the learning climate of the class and improving overall academic performance.

## **DYNAMIC CONSTRUCTION OF SOCIAL NETWORKS IN THE CLASSROOM**

In this chapter, the researchers introduce the dataset used and describe the student identification, seat positioning, student head-up and head-down status identification methods, and the method of constructing in-class social network algorithms based on the dynamics of student classroom seating similarity.

### **Introduction of the Database**

The dataset used in this paper comes from the smart classroom data of a course taken by freshman students at a university. The dataset contains video image data of the thirty-two lessons, basic information data of a total of sixty-eight students in the class (gender, dormitory number, and class committee tenure), student academic achievement data, a list of students' friend nominations, and a list of students' nominations of those individuals that have a negative impact on them (friend nominations and negative friend nominations). The student nomination data were collected by a questionnaire administered to students at the end of the course. In addition, to validate the key student nodes mined in this paper, the first-year GPAs of the students were obtained after six months.

### **Data Acquisition**

In this paper, MTCNN (Zhang et al., 2020) and FaceNet network (Schroff et al., 2015) are used to detect and recognize student faces in the classroom. The input smart classroom image data is first sampled at time T intervals, and face detection is performed on the sampled frame images using MTCNN. Then, the normalized single-face region images are inputted into the face-recognition model

to extract single-face image features. Finally, the recognition results of face images are obtained by a pre-trained classifier to determine student identity information.

Aiming at the student seat recognition in the classroom video, the researchers used a regression model to recognize the students' seats. Firstly, the researchers marked the row of students in the video image of the first class, and then constructed a regression model to identify the rows of students in the subsequent class. In addition, the researchers used HeadPoseEstimate (Guo et al., 2020) to identify the students' head posture in the video of the smart classroom, used a sampling interval of 5s to identify students' head-up and head-down behaviors, and obtained the student classroom head-up rate by calculating the ratio of the number of head-ups to the total number of samples.

To facilitate subsequent experimental analysis, the researchers processed the student friend nomination list and negative friend nomination list in the dataset, respectively, and calculated the number of times each student was nominated as a friend or negative friend by other students, obtaining the number of student friend nominations and negative friend nominations.

### Dynamic Construction Method of In-Class Social Network

While students' single-classroom seating relationships are contingent and random, this paper wants to respond to the interconnectedness among students from their classroom seating relationships. Therefore, the researchers innovatively used multiple classroom seating relationship networks to characterize student relationships, defined student classroom seating similarities, and used them as edge weights to construct in-class social networks.

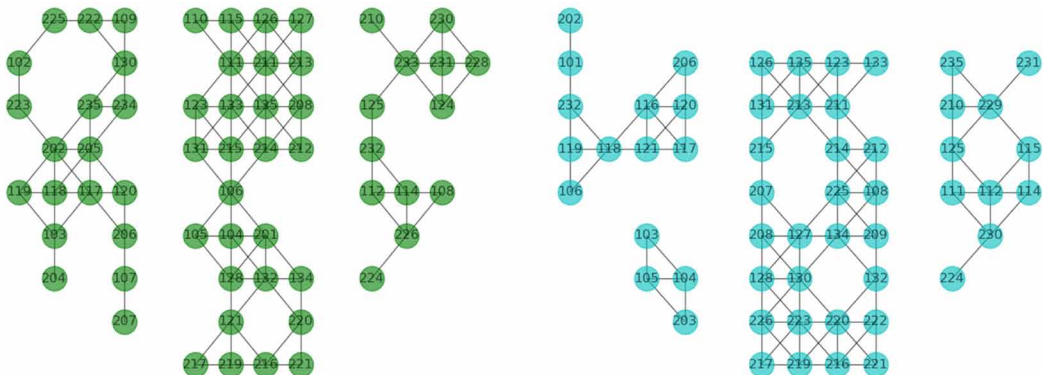
Firstly, this paper constructs multiple undirected and unweighted classroom seating networks, as shown in Figure 1, based on the physical distance relationships of student seats in a classroom. Then, by drawing on the idea of Jaccard similarity, the in-class social network is constructed by defining student classroom seating similarities as the edge weights of student nodes.

The edge weights of two students' in-class social networks (similarity of student seating)  $W_{v_i, v_j}$  are calculated as follows:

$$W_{v_i, v_j} = \sum_{n=0}^N \frac{|S^n(v_i) \cap S^n(v_j)|}{|S^n(v_i) \cup S^n(v_j)|} \quad (1)$$

where  $N$  is the total number of selected classrooms, and  $S^n(v_i)$ ,  $S^n(v_j)$  is the set of neighboring student nodes  $v_i$  and  $v_j$ . For example, the seating similarity of two students, with student ID 217

Figure 1. Schematic diagram of classroom seating network



sitting in the first row and fifth column and student ID 219 sitting in the first row and sixth column shown in Figure 1 is calculated as:

$$W_{217,219} = \sum_{n=\{a,b\}} \frac{|S^n(617) \cap S^n(619)|}{|S^n(617) \cup S^n(619)|} = \frac{1}{4} + \frac{2}{6} = 0.583.$$

### EC-GTOPSIS Node Mining Algorithm

In this paper, the researchers propose an EC-GTOPSIS algorithm, which integrates the information content, conflict, and difference of evaluation indicators through the combination weighting method, and uses a fusion of gray correlation analysis and TOPSIS to improve the problem of homogeneity in the traditional node importance assessment (Çelikbilek & Tüysüz, 2020; Hafezalkotob et al., 2019; Kuo et al., 2008; Xie et al., 2018; Yang et al., 2018). Firstly, the researchers obtain the structural characteristics of the in-class social network (weighted degree centrality, closeness centrality, authority centrality, and eigenvector centrality). Secondly, the researchers combine the entropy weight method and CRITIC objective valuation method to calculate the weight coefficient of structural characteristics. Finally, the researchers use the EC-GTOPSIS multi-decision fusion method to rank the student nodes, and to mine the key nodes in classroom.

#### Feature Selection and Normalization

First, the node characteristics within the in-class social network are selected and normalized, and the node weighted degree centrality, closeness centrality, authority centrality, and eigenvector centrality in the network are selected to form a feature vector matrix  $V$ . The weighted degree centrality visually reflects the connectivity of student nodes with other nodes, the closeness centrality reflects the geometric centrality of student nodes, the authority centrality indicates the connectivity value of student nodes, and the eigenvector centrality shows the importance of the potential value of student nodes:

$$V = \begin{bmatrix} v_1(f_1) & \cdots & v_1(f_m) \\ \vdots & \ddots & \vdots \\ v_n(f_1) & \cdots & v_n(f_m) \end{bmatrix} \quad (2)$$

where  $n$  is the number of student nodes,  $m$  is the number of centralities, and  $v_i(f_j)$  is the value of the centrality index  $f(j)$  of the student node  $v_i$ .

Then, each centrality indicator is normalized to calculate  $X = [x_{ij}]$ , and since all the indicators selected here are positive, the formula is shown in Eq. (3):

$$x_{ij} = \frac{v_i(f_j) - \min(v_1(f_j), \dots, v_n(f_j))}{\max(v_1(f_j), v_2(f_j), \dots, v_n(f_j)) - \min(v_1(f_j), v_2(f_j), \dots, v_n(f_j))} \quad (3)$$

#### Combined Weight Method

This paper combines the entropy weighting method and the CRITIC objective weighting method to form the combined weight. The entropy weighting method is based on information entropy

theory and calculates the weight of each centrality by calculating its information entropy—the smaller the information entropy, the greater the contribution of the centrality to the decision-making of the plan, and correspondingly, the higher its weight. The CRITIC objective weighting method is a method of assigning objective values based on data volatility. The idea is to compare the strength and conflict of the centrality. The strength of comparison is represented by the standard deviation of the centrality. The larger the standard deviation of the centrality, the greater the volatility, and the higher the weight of the assignment. The conflict is represented by the correlation coefficient of the centrality. The larger the correlation coefficient between the centrality indicators, the smaller the conflict, and the lower the weight of the assignment. The specific steps are as follows.

### *CRITIC Objective Weight Calculation Method*

First, the standard deviation  $S_j$  and conflict coefficient  $R_j$  are calculated from the normative centrality index  $X$  from Eq. (3):

$$S_j = \sqrt{\sum_{i=1}^n (x_{ij} - \bar{x}_j)^2 / (n-1)} \quad (4)$$

$$R_j = \sum_{i=1}^n (1 - r_{ij}) \quad (5)$$

In Eq. (4),  $\bar{x}_j = \frac{1}{n} \sum_{i=1}^n x_{ij}$  represents the standard value of the first centrality index; in Eq. (5),  $r_{ij}$  is the Pearson correlation coefficient between the centralities.

Secondly, the variability and conflict of centrality indicators are fused to determine the objective weight  $w_j^c$  of CRITIC:

$$w_j^c = \frac{S_j R_j}{\sum_{j=1}^m S_j R_j} \quad (6)$$

### *Information Entropy Weight Calculation Method*

First, the information entropy  $E_j$  is calculated according to the normalized node centrality obtained by Eq. (3), and then the objective weights  $w_j^e$  are determined by the information entropy:

$$E_j = -\frac{1}{\ln n} \sum_{i=1}^n p_{ij} \ln p_{ij} \quad (7)$$

$$w_j^e = \frac{1 - E_j}{\sum_{j=1}^m (1 - E_j)} \quad (8)$$

where  $p_{ij} = x_{ij} / \sum_{i=1}^n x_{ij}$ , if  $p_{ij} = 0$  then define  $\lim_{p_{ij} \rightarrow 0} p_{ij} \ln p_{ij} = 0$ .

### Combination Weight Determination Method

The combination weight will be based on the ideal point theory (Qiangqiang et al., 2015); that is, the vector objective function will be combined with the deviation from the ideal point of the problem being considered, combining the entropy weights and the CRITIC objective weights.

The objective weights  $w^e = (w_1^e, w_2^e, w_3^e, \dots, w_n^e)$  determined based on entropy weighted method, and the objective weights  $w^c = (w_1^c, w_2^c, w_3^c, \dots, w_n^c)$  calculated by CRITIC are combined to obtain the total weight value  $w_1 = (w_1, w_2, w_3, \dots, w_n)$ . Meanwhile, the ideal value of each centrality indicator is defined as  $x_j^* (j = 1, 2, 3, \dots, n)$ , and the ideal solution of the system is defined as  $A = (w_1 x_1^*, w_2 x_2^*, w_3 x_3^*, \dots, w_n x_n^*)$ . The formula for the distance from solution  $i$  to the ideal point is:

$$dis_i = \sqrt{\sum_{j=1}^n w_j^2 (x_{ij} - x_j^*)^2} \quad (9)$$

The smaller the distance  $dis_i$ , the closer the resulting figure is to the ideal solution. To minimize the deviation of the weight values of the combined assignment, the following nonlinear programming model can be constructed:

$$f(w') = [dis_i^2(w') - dis_i^2(w^{e'})]^2 + [dis_i^2(w') - dis_i^2(w^{c'})]^2 \quad (10)$$

where:

$$w' = \frac{w}{\sqrt{w_1^2 + w_2^2 + \dots + w_n^2}}$$

$$w^{e'} = \frac{w^e}{\sqrt{w_1^{e2} + w_2^{e2} + \dots + w_n^{e2}}}$$

$$w^{c'} = \frac{w^c}{\sqrt{w_1^{c2} + w_2^{c2} + \dots + w_n^{c2}}}$$

According to the Lagrange multiplier method, the optimization problem above can be solved, and the result is:

$$w'_j = \sqrt{\frac{(w^{e'})^2 + (w^{c'})^2}{2}}, \quad j = 1, 2, \dots, n \quad (11)$$

Therefore, the combination weight coefficient can be calculated by Eq. (12):

$$w_j = \frac{w'_j}{\sum_{j=1}^n w'_j}, \quad j = 1, 2, \dots, n \quad (12)$$

### Student Node Ranking

In this paper, the researchers use the GTOPSIS method to rank the nodes of in-class social networks. GTOPSIS measures the relevance between nodes mainly based on the similarity or dissimilarity of the development trends among their features and improves the relative proximity of the solution to the optimal solution in the traditional TOPSIS method (Zhang et al., 2021). The specific operational steps are as follows:

1. Based on the centrality matrix  $X$  obtained from Eq. (3) and the combined weight matrix  $W$  obtained from Eq. (12), construct the weighted normalization matrix  $Z = [z'_{ij}]$ :

$$Z = X \times W = \begin{bmatrix} w_1 x_{11} & \cdots & w_m x_{1m} \\ \vdots & \ddots & \vdots \\ w_1 x_{n1} & \cdots & w_m x_{nm} \end{bmatrix} \quad (13)$$

2. Determine the positive and negative ideal solutions of each centrality index  $Z^+, Z^-$ :

$$Z^+ = \left\{ \max_{i \in 1, 2, \dots, n} \{Z_{i1}\}, \dots, \max_{i \in 1, 2, \dots, n} \{Z_{im}\} \right\} = \{Z_1^+, \dots, Z_m^+\} \quad (14)$$

$$Z^- = \left\{ \max_{i \in 1, 2, \dots, n} \{Z_{i1}\}, \dots, \max_{i \in 1, 2, \dots, n} \{Z_{im}\} \right\} = \{Z_1^-, \dots, Z_m^-\} \quad (15)$$

3. Calculate the distance of node centrality from the ideal solution  $d^+$  and the distance from the negative ideal solution  $d^-$ :

$$d_i^+ = \sqrt{\sum_{j=1}^m (z_{ij} - Z_j^+)^2}, d_i^- = \sqrt{\sum_{j=1}^m (z_{ij} - Z_j^-)^2} \quad (16)$$

4. Calculate the gray correlation coefficient matrix between the centrality of each node and the positive and negative ideal solutions  $G^+, G^-$ :

$$G^+ = (g_{ij}^+)_{n \times m}, G^- = (g_{ij}^-)_{n \times m} \quad (17)$$

$$g_{ij}^+ = \frac{|Z_j^+ - Z_{ij}|_{\min} + \rho |Z_j^+ - Z_{ij}|_{\max}}{|Z_j^+ - Z_{ij}| + \rho |Z_j^+ - Z_{ij}|_{\max}} \quad (18)$$

$$g_{ij}^- = \frac{|Z_j^- - Z_{ij}|_{\min} + \rho |Z_j^- - Z_{ij}|_{\max}}{|Z_j^- - Z_{ij}| + \rho |Z_j^- - Z_{ij}|_{\max}} \quad (19)$$

where  $\rho \in [0, 1]$  is the resolution coefficient, and the larger its value, the greater the resolution factor. The experiment shows that the correlation coefficient reflects the maximum amount of node information when its value is 0.5.

5. Calculate the gray correlation coefficients between the centrality of each node and the positive and negative ideal solutions  $g_i^+$ ,  $g_i^-$ :

$$g_i^+ = \frac{1}{m} \sum_{j=1}^m g_{ij}^+, \quad g_i^- = \frac{1}{m} \sum_{j=1}^m g_{ij}^- \quad (20)$$

6. Calculate the relative proximity  $Q_i^+$ ,  $Q_i^-$ , after quantizing the distance calculated by Eq. (16) and the gray correlation calculated by Eq. (20):

$$D_i^+ = \frac{d_i^+}{(d_i^+)_{\max}}, \quad D_i^- = \frac{d_i^-}{(d_i^-)_{\max}} \quad (21)$$

$$G_i^+ = \frac{g_i^+}{(g_i^+)_{\max}}, \quad G_i^- = \frac{g_i^-}{(g_i^-)_{\max}} \quad (22)$$

$$Q_i^+ = \alpha D_i^- + \beta G_i^+, \quad Q_i^- = \alpha D_i^+ + \beta G_i^- \quad (23)$$

where  $\alpha + \beta = 1$ ,  $0 \leq \alpha \leq 1$ ,  $0 \leq \beta \leq 1$ ,  $\alpha$  and  $\beta$  are used to balance the scoring weights of the scenarios by gray correlation analysis and TOPSIS, and it is experimentally proven that the best results are achieved when their values are taken as 0.5.  $Q_i^+$  and  $Q_i^-$  reflect the distance between each node and the ideal value from both positive and negative sides.

Then, the relative proximity of nodes  $N_i$  is calculated by Eq. (24):

$$N_i = \frac{Q_i^+}{Q_i^+ + Q_i^-} \quad (24)$$

Finally, the nodes are sorted in descending order according to the value of the  $N_i$ . The larger the relative proximity, the closer the node is to the core of the network.

## EXPERIMENTAL RESULTS AND ANALYSIS

### Experimental Process

The researchers propose an EC-GTOPSIS negative nodes mining algorithm based on the node characteristics of in-class social networks. First, the researchers construct in-class social networks based on the student classroom seating similarities. Then, the structural characteristics of the in-class social network are analyzed, and the student nodes are sorted and grouped by EC-GTOPSIS multi-decision fusion method. The negative nodes are mined by combining information such as academic performance, friendships, and negative friend nominations of student nodes. Finally, the effectiveness

of the algorithm proposed in this paper is verified by SIR Epidemic experiments and comparative validation experiments. The overall block diagram is shown in Figure 2.

### Construction and Characteristic Analysis of In-Class Social Network

Since in-class social networks are constructed based on the similarity of students' seating relationships at different times in the same space, classroom video data from three to eight classes are selected for in-class social network construction in this paper, and part of the display is shown in Figure 3. As the number of classes used increases, the connection density between nodes increases significantly, and the number of triads in the network becomes greater.

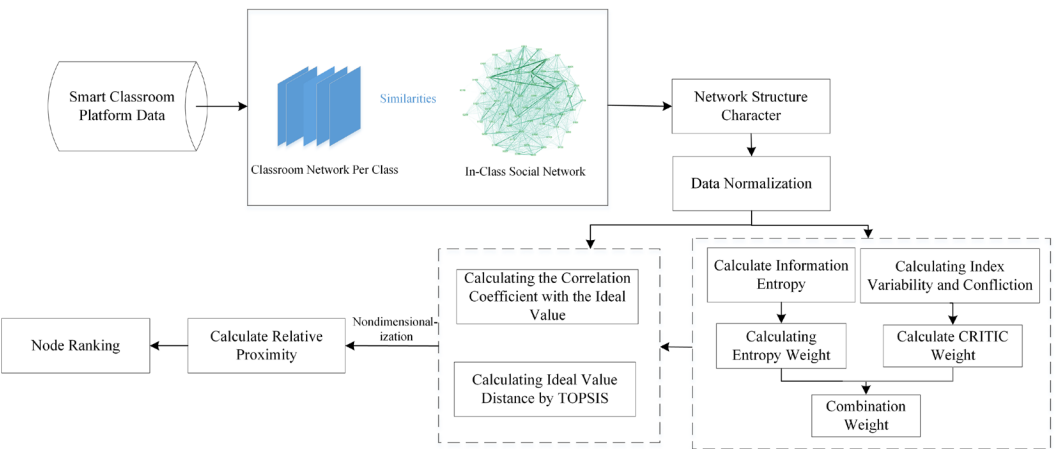
At the same time, the researchers analyze the structural characteristics of the in-class social network, and the main structural characteristics are shown in Table 1. As the number of classes used in the network increases, its average network degree, average weighted degree, and network density gradually increase, while the network diameter gradually decreases. The node degree reflects the connection of nodes to other nodes within the in-class social network, and the larger the value, the more connections exist between nodes and other nodes in the network. The weighted degree further reflects how closely the node is connected to other nodes based on the node degree. The clustering coefficient is a quantitative representation of the probability that the neighboring student nodes are neighbors of each other, and to some extent it reflects the sparsity of students' seats in class. The smaller the average clustering coefficient, the more sparsely students are seated in the classroom. Network density reflects the degree of completion of the in-class social network, and the higher the value, the stronger the overall network connectivity.

### Mining and Analysis of Key Student Nodes

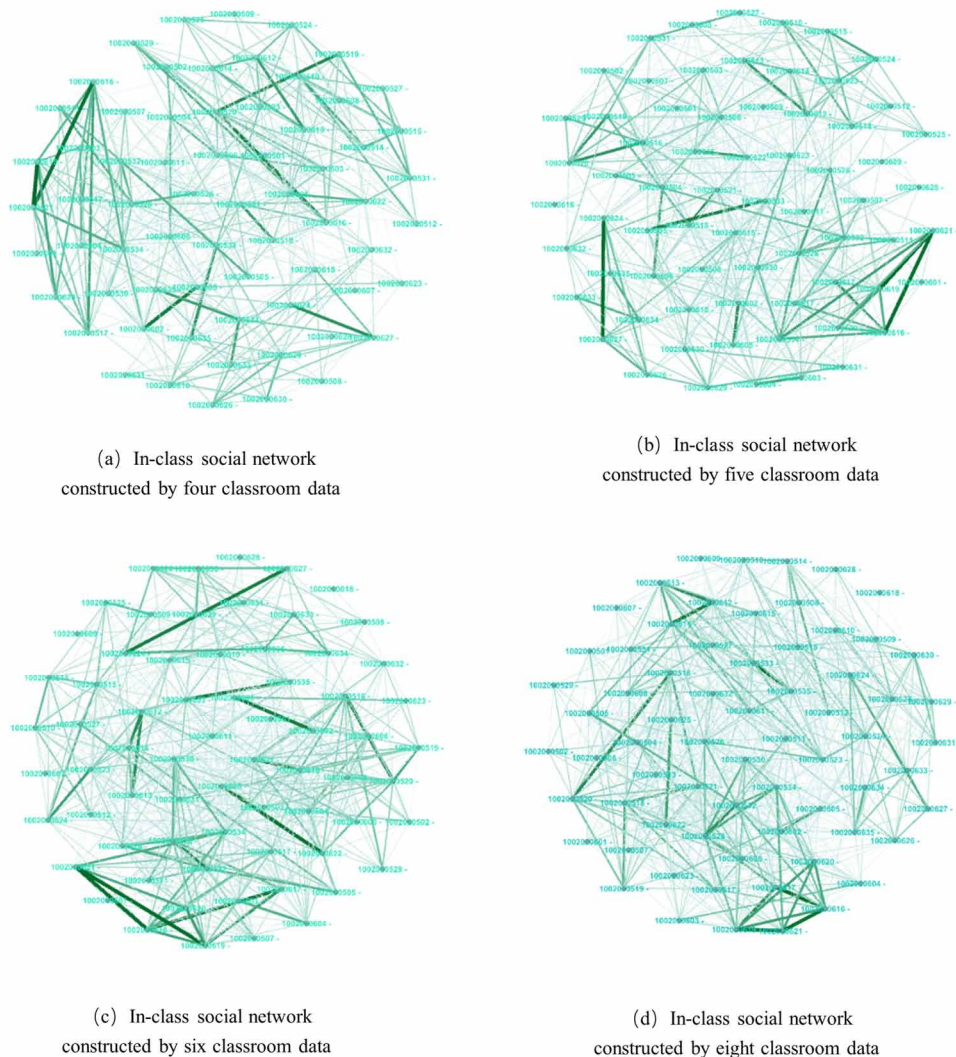
In this section, in-class social networks are constructed using eight classes, and the EC-GTOPSIS multi-decision algorithm is used to rank and group student nodes. Then, the researchers analyze the relations between the node ranking results of this class social network and academic performance, friend nomination, classroom interaction behavior, and negative friend nomination; and then mine the key nodes with negative effects. Finally, the researchers verify the findings of this chapter by conducting an experimental comparison using students' first-year GPAs and class committee tenures.

Based on the network, node centrality calculations are performed, and several representative centralities are extracted (weighted degree centrality, closeness centrality, authority centrality, and eigenvector centrality). The EC-GTOPSIS algorithm is then used to rank the nodes. The results are partially shown in Table 2.

Figure 2. Block diagram of EC-GTOPSIS



**Figure 3. Schematic diagram of in-class social network with different number of classes**



**Table 1. Structural characteristics of in-class social networks constituted by different numbers of classes**

| Number of Classes Used      | 3      | 4      | 5      | 6      | 7      | 8      |
|-----------------------------|--------|--------|--------|--------|--------|--------|
| Network average degree      | 14.303 | 17.394 | 19.559 | 22.676 | 25.412 | 27.735 |
| Average weighted degree     | 7.155  | 9.395  | 11.076 | 13.634 | 16.405 | 18.931 |
| Network density             | 0.22   | 0.268  | 0.292  | 0.338  | 0.379  | 0.414  |
| Average cluster coefficient | 0.584  | 0.569  | 0.572  | 0.573  | 0.593  | 0.599  |
| Network diameter            | 5      | 3      | 3      | 3      | 3      | 3      |
| Minimum degree              | 2      | 3      | 5      | 5      | 5      | 5      |

**Table 2. Nodes ranking results**

| ID    | Weighted Degree | Closeness Centrality | Authority Centrality | Eigenvector Centrality | Relative Proximity | Ranking Results |
|-------|-----------------|----------------------|----------------------|------------------------|--------------------|-----------------|
| 0134  | 29.317          | 0.710                | 0.183                | 0.966                  | 0.806              | 1               |
| 0121  | 30.493          | 0.710                | 0.174                | 0.919                  | 0.806              | 2               |
| 0130  | 27.299          | 0.732                | 0.189                | 1.000                  | 0.801              | 3               |
| 0132  | 31.696          | 0.683                | 0.173                | 0.913                  | 0.794              | 4               |
| 0128  | 33.124          | 0.670                | 0.168                | 0.886                  | 0.785              | 5               |
| ..... | .....           | .....                | .....                | .....                  | .....              | .....           |
| 0102  | 8.303           | 0.542                | 0.050                | 0.263                  | 0.313              | 64              |
| 0227  | 10.185          | 0.522                | 0.036                | 0.197                  | 0.299              | 65              |
| 0228  | 6.141           | 0.542                | 0.040                | 0.217                  | 0.281              | 66              |
| 0129  | 6.518           | 0.493                | 0.035                | 0.185                  | 0.244              | 67              |
| 0218  | 1.894           | 0.477                | 0.015                | 0.079                  | 0.164              | 68              |

Finally, the student nodes in the network are divided into seven groups according to the ranking results, and then the differences in academic performance, number of friend nominations, classroom interaction behaviors, and number of negative friend nominations are calculated and compared for each group, as shown in Table 3 and Figure 4.

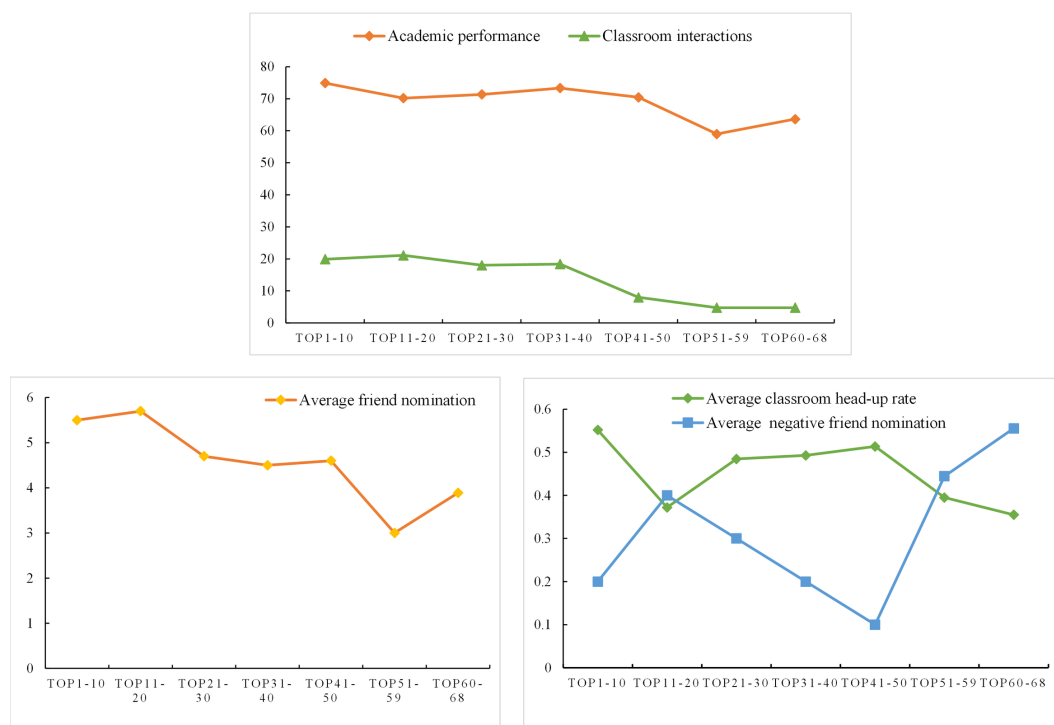
The experiment concludes the following points: (i) The two lowest-ranked groups are the invisible negative nodes, who are on the edge of the networks and at risk of failing their final exams. They have extremely low academic performance and classroom interaction counts, and extremely high negative friend nominations. Their low number of classroom interactions meant that they did not significantly disturb others in class, yet their negative friend nominations far exceeded those of the other groups, suggesting that students with negative effects in the classroom environment are not only students with explicit disturbance behaviors, but also students who are likely to be on the edge of the classroom, less motivated in class, or even exhibit serious truancy and absence behaviors. (ii) The second group are the key nodes that are in the center of the network and have a strong dominant negative influence in the classroom. Their academic performance is

**Table 3. Average basic situation in seven groups**

| Sort      | Academic Performance | Classroom Interactions | Number of Friend Nominations | Classroom Head-Up Rate | Number of Negative Friend Nominations |
|-----------|----------------------|------------------------|------------------------------|------------------------|---------------------------------------|
| Top 1–10  | 74.896               | 19.9                   | 5.5                          | 0.552                  | 0.2                                   |
| Top 11–20 | 70.194               | 21.1                   | 5.7                          | 0.372                  | 0.4                                   |
| Top 21–30 | 71.359               | 18                     | 4.7                          | 0.485                  | 0.3                                   |
| Top 31–40 | 73.334               | 18.4                   | 4.5                          | 0.492                  | 0.2                                   |
| Top 41–50 | 70.466               | 8                      | 4.6                          | 0.514                  | 0.1                                   |
| Top 51–59 | 58.984               | 4.778                  | 3                            | 0.395                  | 0.444                                 |
| Top 60–68 | 63.631               | 4.778                  | 3.889                        | 0.355                  | 0.556                                 |

Note. The values in the table are the average of each group of students.

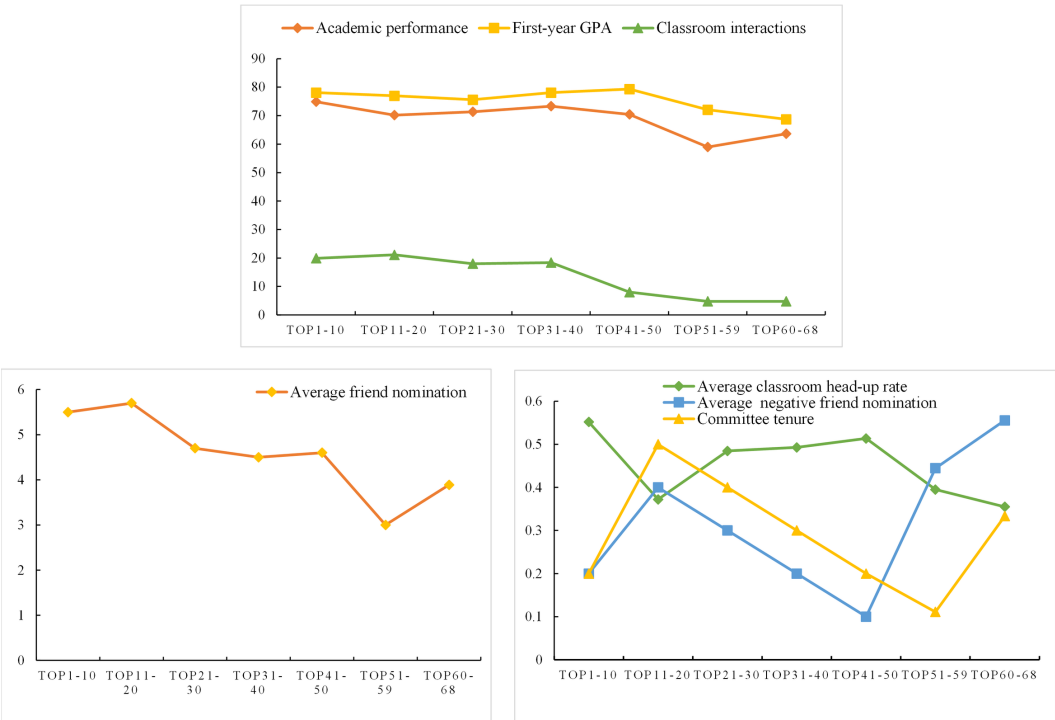
**Figure 4. Seven groups of academic performance, classroom interaction, classroom student head-up rate, average number of negative friend nominations, and number of friend nominations line chart**



average, and they have a lower head-up rate in class but the highest friend nominations, indicating that this group of students have better social resources. A comparison with the second group and the sixth group reveals that they are similar in terms of classroom head-up rate and the number of negative friend nominations, but the second group have a higher network centrality than the sixth group of students, while performing better academically. (iii) The first group are the positive nodes that were very active with driving the classroom atmosphere. They have the highest academic performance scores, the highest classroom head-up rate, low negative friend nominations and high friend nominations, and are the top students who have excellent grades, are focused in class, and have many friends.

To further verify the above findings, the researchers conducted an experiment using the first-year GPAs and class committee tenures of all students in the class, as shown in Figure 5. The experiment shows that the overall trend of first-year GPA is decreasing and consistent with the academic performance of the course, and the first group still performs the best throughout the academic year, while the last two groups perform the worst. The last group, despite barely passing the course test, performed the worst on exams throughout the school year; and up to one-third of them served on class committees, which likely contributed to their levels of friend nominations. Nonetheless, there are students who felt they had a negative influence during the class (as many as 67% of the class members in the last group were nominated as negative friends). At the same time, the class committee tenure strongly verifies the conclusion that the second group are the nodes of dominant negative influence in the classroom. Up to 50% of the students in this group serve on the class committee, and they have far more friend nominations than others, which indicates that they have far more social resources and influence than the other groups of students.

Figure 5. Line chart of GAPs and class assignments in the first year among seven groups



## SIR Epidemic Model Experiments and Comparative Validation Experiments

To further verify the effectiveness of the proposed EC-GTOPSIS algorithm in identifying key nodes within in-class social networks, this section uses the SIR epidemic model to simulate the spread of information within in-class social networks and compares it with the Entropy-weighted GRA-TOPSIS (E-GTOPSIS), the CRITIC-weighted GRA-TOPSIS (C-GTOPSIS), and the Entropy-CRITIC combined weighted TOPSIS (EC-TOPSIS) algorithms. In the experiment, the top-ranked node in the algorithm was taken as the initial source of propagation, with a network infection probability of 0.2, an immunity probability of 0.05, and a weighted network propagation threshold of 1.2. The average propagation rate of infected nodes in the network was calculated over 1000 propagation experiments and compared with the number of iterations, as shown in Figure 6.

As shown in the Figure 6, although the EC-GTOPSIS algorithm was very close to the EC-TOPSIS algorithm in the initial stage of the propagation, and could not exceed the EC-TOPSIS algorithm in the middle stage of the propagation, the algorithm had the highest propagation rate for its sorted nodes when the propagation reached stability.

As the main purpose of constructing the in-class social network is to mine students with negative impacts, it is difficult to demonstrate the superiority of the algorithm solely from the perspective of the infectious disease simulation experiment. Therefore, the academic performance and the first-year GPAs of the student nodes ranked by the four algorithms will be compared to demonstrate the effectiveness of the proposed algorithm in identifying key negative nodes. The results of the experimental comparison are shown in Table 4.

As seen in Table 4, the four multi-criteria fusion algorithms can effectively rank and group student nodes, and there is a significant downward trend in the academic performance of student nodes between groups. Comparing the academic performance and first-year GPAs of Group 1 with Groups

Figure 6. Comparison chart of propagation rates of SIR infectious disease models

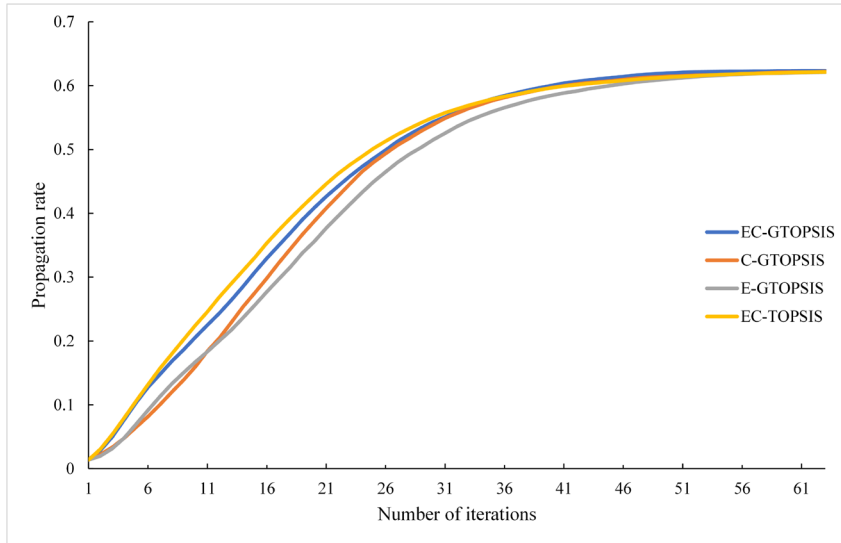


Table 4. Results of comparison of the academic performance and first-year GPA of four algorithms

| Group | Academic Performance |              |           |              | First-Year GPA |              |           |              |
|-------|----------------------|--------------|-----------|--------------|----------------|--------------|-----------|--------------|
|       | EC-GTOPSIS           | C-GTOPSIS    | E-GTOPSIS | EC-TOPSIS    | EC-GTOPSIS     | C-GTOPSIS    | E-GTOPSIS | EC-TOPSIS    |
| 1     | <b>74.90</b>         | 67.83        | 71.02     | <b>74.90</b> | 78.08          | <b>79.07</b> | 76.44     | 78.08        |
| 2     | 70.19                | 77.04        | 74.07     | 70.19        | 76.99          | 78.06        | 78.63     | 76.99        |
| 3     | 71.36                | 65.61        | 72.70     | 69.62        | 75.60          | 70.50        | 75.09     | 75.72        |
| 4     | 72.14                | 64.37        | 71.39     | 74.08        | 78.04          | 72.28        | 78.14     | 77.91        |
| 5     | 70.47                | 70.63        | 67.92     | 71.84        | 79.32          | 76.26        | 77.86     | 78.17        |
| 6     | <b>58.98</b>         | 74.24        | 61.98     | 59.65        | <b>72.05</b>   | 80.08        | 72.61     | 73.44        |
| 7     | 63.63                | <b>62.86</b> | 63.47     | 63.63        | <b>68.71</b>   | 72.71        | 69.77     | <b>68.71</b> |

Note. Groups 1 to 7 represent the serial number of the seven groups of students classified by the corresponding algorithm.

6 and 7 students, it is found that although the seventh group of students ranked by the EC-GTOPSIS algorithm performed slightly worse in the final exam scores than those ranked by the C-GTOPSIS algorithm, as a whole, students grouped by the EC-GTOPSIS algorithm had the greatest difference in final exam scores between the first and last two groups, which could better distinguish student nodes. Moreover, students in Groups 6 and 7 under the EC-GTOPSIS algorithm not only performed much worse than other student nodes in academic performance for the course, but also had the worst overall exam performance in their first year.

## CONCLUSION

In this paper, to improve the traditional single empirical student evaluation model and transform it into a process-based evaluation grounded in an in-class social network, the researchers propose a dynamic in-class social network construction method established out of student seating similarity, and an EC-GTOPTSIS multi-decision fusion method created from the combined weights of network

characteristics to mine the key nodes within the in-class social network. It is proved through experiments that the method can mine the student nodes with positive influence, explicit negative influence, and invisible negative influence within the in-class social network. In the future, it will be further combined with student behavior data such as students' postures and expressions, and teachers' knowledge points that allow mining of their inner connections, thus not only further improving the student evaluation system, but also providing ideas for the improvement of teachers' evaluation systems.

## **CONFLICT OF INTEREST**

The authors of this publication declare there are no competing interests.

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