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Privacy-Aware Examination Results Ranking for the Balance Between Teachers and Mothers

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Abstract: As the main parent and guardian, mothers are often concerned with the study performance of their children. More specifically, most mothers are eager to know the concrete examination scores of their children. However, with the continuous progress of modern education systems, most schools or teachers have now been forbidden to release sensitive student examination scores to the public due to privacy concerns, which has made it infeasible for mothers to know the real study level or examination performance of their children. Therefore, a conflict has come to exist between teachers and mothers, which harms the general growing up of students in their study. In view of this challenge, we propose a Privacy-aware Examination Results Ranking (PERR) method to attempt at balancing teachers' privacy disclosure concerns and the mothers' concerns over their children's examination performance. By drawing on a relevant case study, we prove the effectiveness of the proposed PERR method in evaluating and ranking students according to their examination scores while at the same time securing sensitive student information.

Key words: user privacy protection; evaluation and ranking; perfeormance balance

1 Introduction

In modern family relations, father and mother often play a key role in the educational development of their children. More specifically, it has become commonplace to place more educational responsibility on mothers as they are generally regarded as "more professional" in their children's education. Thus, for a child who is studying at a school, his or her mother usually co-operates with teachers to promote the child's education activities or possible issues[1, 2]. In effect, globally speaking, mothers and teachers could be seen as the main guardians of students. At present, these two groups play a pivotal role in education.

To monitor the studying effects of students, mothers are often eager to know the students' studying behavior and states at school. One of the most effective ways to get to know the overall school performance of students is examination scores. According to the examination performance, a mother can enact appropriate study improvement plans or strategies for her child to fix the drawbacks or mistakes existing in current study patterns or methods[3–5]. Yet, with the continuous progress of modern education systems, most schools or teachers are now not allowed to open the concrete student examination scores in public due to possible privacy concerns[6–10]. In this situation, it has become increasingly difficult for a mother to know the real study level or examination performance of her children. Moreover, students themselves are often not willing to tell their parents their concrete examination score or

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other performance due to various reasons.

In this situation, an inherent conflict has come to exist between teachers and mothers, which harms the growing up of most students in terms of both study at school and life at home. In view of this challenge, a Privacy-aware Examination Results Ranking (PERR) method is proposed in this paper to try our best to balance the teachers' privacy disclosure concerns and the mothers' concerns on examination performance. By drawing on a relevant case study, we prove the effectiveness of the proposed PERR method in evaluating and ranking students according to their examination scores while securing sensitive student information.

In summary, the contribution in this paper is two-fold.

(1) We introduce an objective and privacy-aware evaluation technique, i.e., TOPSIS, into our focused examination performance evaluation problems. Then, we put forward a TOPSIS-based examination performance ranking method, i.e., PERR. By critically analyzing PERR, in turn, we can achieve a good tradeoff (or balance) between teachers' privacy disclosure concerns and mothers' concerns over examination performance.

(2) To evaluate the feasibility and effectiveness of the PERR method, we introduce a case study to elaborate on the concrete process and procedure of our proposed algorithm. This case study then validates the effectiveness of PERR.

The remaining structure of this research paper is as follows: In Section 2, an intriguing example from the real world is presented to further describe the motivation and research significance of our proposal. In Section 3, concrete steps and procedures are described in more detail. In Section 4, a real-world case study regarding examination performance evaluation is introduced to ease the algorithmic understanding for readers. In Section 5, further discussions are presented. Finally, in Section 6, we conclude this paper by pointing out some possible future work scenarios in upcoming educational research.

2 Motivation

A concrete example is presented here to demonstrate the research significance of this paper. As Fig. 1 clearly indicates, the example involves three students (John, Alex, and Lily) and their respective examination performances in three courses (English, Sport, and Nature). For example, Alex's examination scores or

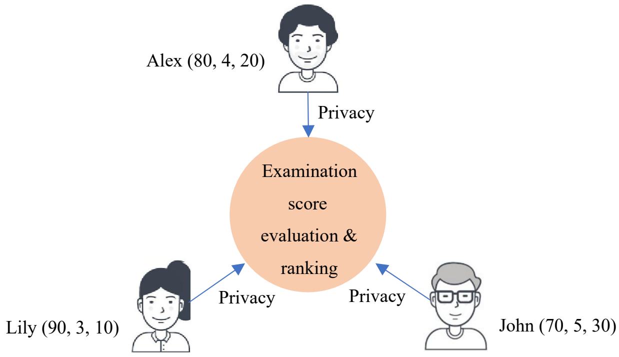

Fig. 1 Two challenges in examination score evaluation and ranking: diverse data scale and privacy leakage.

performance of the three courses are 80, 4, and 20. Here, the score ranges for the three courses are different. In concrete terms, English score range is [0, 100], Sport score range is [0, 5], and Nature score range is [0, 30]. Such diverse data scales from different courses often make it hard to fairly and objectively evaluate the examination performance of these students. In addition, examination scores or performance could be considered as a kind of private information for students. Therefore, although the three students are willing to share their examination scores with the central score evaluation and ranking agency, the agency should have the aim of protecting their privacy. Here, motivated by the above-mentioned two challenges, PERR is suggested. In the following sections of this paper, a more detailed procedure on the subject will be elaborated with an in-depth analysis and relevant discussions.

3 PERR

The PERR method mainly consists of four distinct steps, as illustrated in Fig. 2. We assume that there are m students ($stu_1, \ldots, stu_m$) and n courses ($cou_1, \ldots, cou_n$).

Step 1: Data normalization

According to the known n examination scores of m students, we can construct an $m \times n$ matrix $\boldsymbol{M}$ in the following:

$$\boldsymbol{M}: \begin{array}{c} \\ stu_1 \\ \vdots \\ stu_m \end{array} \begin{array}{c} \begin{array}{ccc} cou_1 & \ldots & cou_n \end{array} \\ \begin{bmatrix} v_{1,1} & \cdots & v_{1,n} \\ \vdots & \ddots & \vdots \\ v_{m,1} & \cdots & v_{m,n} \end{bmatrix} \end{array} \tag{1}$$

where $v_{i,j}$ denotes student stu_i's score over course cou_j.

As shown in Fig. 1, the value ranges for all courses are not the same. Thus, we need to normalize all the score values in matrix $\boldsymbol{M}$ for the simplicity of the subsequent processing. In concrete terms, we utilize the following

Step 1: Data normalization
For each course, we normalize the course scores for all students into a normalized value belonging to [0, 1].
Step 2: Determine Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS)
For each course involved in PERR, we can determine their maximum and minimum values. Then, according to these values, we construct *PIS* and *NIS*.
Step 3: Evaluate each student based on *PIS* and *NIS*
For each student, we can calculate the distance between their examination scores and *PIS* (denoted by D^+), the distance between their examination scores and *NIS* (denoted by D^-). Then, according to D^+ and D^-, each student is assigned a concrete score evaluation value.
Step 4: Rank all students in descending order
According to the derived evaluation scores of all students, we can rank them in a descending order.

Fig. 2 Major procedure of PERR method.

normalization formula to achieve the above-mentioned purpose:

$$\varphi_{i,j} = \frac{v_{i,j}}{\sqrt[2]{\sum_{k=1}^{m}(v_{k,j})^2}} \tag{2}$$

Through Eq. (2), we can convert each $v_{i,j}$ value in matrix $\boldsymbol{M}$ into a normalized $\varphi_{i,j}$ belonging to [0, 1].

Step 2: Determine PIS and NIS

For each course involved in PERR, we can determine their maximum and minimal normalized values according to all student scores and performance. Then, according to these values related to n courses, we can construct a *PIS* and an *NIS*. The concrete generation processes of *PIS* and *NIS* are formalized by the following equations:

$$PIS = (Max_1, Max_2, \ldots, Max_n) \tag{3}$$

$$Max_j = \max\left\{\varphi_{1,j}, \ldots, \varphi_{m,j}\right\} (1 \leqslant j \leqslant n) \tag{4}$$

$$NIS = (Min_1, Min_2, \ldots, Min_n) \tag{5}$$

$$Min_j = \min\left\{\varphi_{1,j}, \ldots, \varphi_{m,j}\right\} (1 \leqslant j \leqslant n) \tag{6}$$

Here, scores are of "larger is better" property. Therefore, *PIS* is constituted by the maximum normalized values of n courses $Max_j (1 \leqslant j \leqslant n)$ and *NIS* is constituted by the minimum normalized values of n courses $Min_j (1 \leqslant j \leqslant n)$. In addition, please note that Eqs. (3)–(6) are only suitable for creating the *PIS* and *NIS*, like examination scores. If the dimensions are negative (e.g., time cost, delay, and price), the *PIS* and *NIS* can be created based on Eqs. (4) and (6)–(8),

$$PIS = (Min_1, Min_2, \ldots, Min_n) \tag{7}$$

$$NIS = (Max_1, Max_2, \ldots, Max_n) \tag{8}$$

Step 3: Evaluate each student based on *PIS* and *NIS*

For each student $stu_i (1 \leqslant i \leqslant m)$, we can model his or her examination performance with a vector constituted by the normalized score values $\varphi_{i,j}$ corresponding to courses cou_j $(1 \leqslant j \leqslant n)$. For instance, $stu_1(\varphi_{1,1}, \ldots, \varphi_{1,n})$, $stu_2(\varphi_{2,1}, \ldots, \varphi_{2,n})$, and so on. Next, we calculate the distance between each student stu_i and *PIS*,

$$D_{i+} = Dist(stu_i, PIS) = \sqrt[2]{\sum_{j=1}^{n}(\varphi_{i,j} - Max_j)^2} \tag{9}$$

Furthermore, we calculate the distance between each student stu_i and *NIS*,

$$D_{i-} = Dist\,(stu_i, NIS) = \sqrt[2]{\sum_{j=1}^{n}(\varphi_{i,j} - Min_j)^2} \tag{10}$$

Intuitively, for a student $stu_i (1 \leqslant i \leqslant m)$, we often expect a small D_i^+ and a large D_i^-. Inspired by this observation, we use D_i to depict the overall performance of stu_i,

$$D_i = \frac{D_{i-}}{D_{i+} + D_{i-}} \tag{11}$$

Moreover, D_i is of "larger is better" property.

Step 4: Rank all students in a descending order

As analyzed in Step 3, each student $stu_i (1 \leqslant i \leqslant m)$ is assigned a D_i value to quantify the examination performance of stu_i. The larger the D_i is, the better the stu_i performs in an examination. Thus, according to the D_i values of students, we can rank all students in a descending order. Then, we can release the concrete ranking to the mothers who care about the studying level of their children. This way, the private information of students is preserved. In particular, we have achieved a good tradeoff (or balance) between teachers and mothers.

Furthermore, each student's examination score is only compared with *PIS* and *NIS* directly, without comparing them with the examination scores of other students. This way, the sensitive examination scores of students are well protected. Importantly, this is the reason why we claim that our proposed PERR method can also secure user privacy.

Our proposed PERR method can be specified more intuitively with Algorithm 1.

4 Case Study

In this section, a case study extracted from the example in Fig. 1 is offered to demonstrate the concrete running process of our proposed PERR method. Next, we

Algorithm 1 PERR

Input: (1) m students: $stu_1, \ldots, stu_m$
(2) n courses: $cou_1, \ldots, cou_n$
(3) matrix $\boldsymbol{M}$: $v_{i,j}$ $(1 \leqslant i \leqslant m, 1 \leqslant j \leqslant n)$
Output: (1) Student ranking list: SRL
for $j = 1$ to n **do**
  $sum_j = 0$
  for $i = 1$ to m **do**
    $sum_j = sum_j + v_{i,j}^2$
  end for
  $sum_j = (sum_j)^{1/2}$
  for $i = 1$ to m **do**
    $\varphi_{i,j} = v_{i,j} / sum_j$
  end for
end for
for $j = 1$ to n **do**
  for $i = 1$ to m **do**
    $Max_j = \max\{\varphi_{1,j}, \ldots, \varphi_{m,j}\}$
    $Min_j = \min\{\varphi_{1,j}, \ldots, \varphi_{m,j}\}$
  end for
end for
$PIS = (Max_1, Max_2, \ldots, \mathrm{Max}_n)$
$NIS = (Min_1, Min_2, \ldots, Min_n)$
for $i = 1$ to m **do**
  Calculate D_i+ based on Eq. (9)
  Calculate D_i- based on Eq. (10)
  $D_i = D_i - /(D_i - + D_i +)$
end for
Rank $stu_i (1 \leqslant i \leqslant m)$ in a descending order based on D_i
Put ordered stu_i $(1 \leqslant i \leqslant m)$ into SRL
Return SRL

introduce PERR according to the four steps specified in Fig. 2.

Step 1: Data normalization

According to the example in Fig.1, a student-course performance matrix $\boldsymbol{M}$ is as follows:

$$\boldsymbol{M}: \begin{array}{c} \\ \text{John} \\ \text{Alex} \\ \text{Lily} \end{array} \begin{array}{c} \begin{array}{ccc} \text{English} & \text{Sport} & \text{Nature} \end{array} \\ \left[\begin{array}{ccc} 70 & 5 & 30 \\ 80 & 4 & 20 \\ 90 & 3 & 10 \end{array}\right] \end{array} \tag{12}$$

In concrete terms, M contains the examination scores of the three students over three courses. We normalize the score values of three columns according to Eq. (2). Afterwards, we are able to get a new normalized matrix $\boldsymbol{M}^{\#}$,

$$\boldsymbol{M}^{\#}: \begin{array}{c} \\ \text{John} \\ \text{Alex} \\ \text{Lily} \end{array} \begin{array}{c} \begin{array}{ccc} \text{English} & \text{Sport} & \text{Nature} \end{array} \\ \left[\begin{array}{ccc} 0.50 & 0.71 & 0.80 \\ 0.58 & 0.57 & 0.53 \\ 0.65 & 0.42 & 0.27 \end{array}\right] \end{array} \tag{13}$$

Step 2: Determine *PIS* and *NIS*

As normalized examination scores in matrix $\boldsymbol{M}^{\#}$ are all positive dimensions, we determine *PIS* and *NIS* based on Eqs. (3)–(6) and (13). In concrete terms, *PIS* and *NIS* are shown below:

$$PIS = (0.65, 0.71, 0.80) \tag{14}$$

$$NIS = (0.50, 0.42, 0.27) \tag{15}$$

Step 3: Evaluate each student based on *PIS* and *NIS*

As Eq. (13) shows, the normalized examination scores of the three students can be represented by John (0.50, 0.71, 0.80), Alex (0.58, 0.57, 0.53), and Lily (0.65, 0.42, 0.27). Next, we calculate the distance of these three students with *PIS*,

$$\begin{aligned} D_{\text{John}+} &= Dist\,((0.50, 0.71, 0.80), \\ &\quad (0.65, 0.71, 0.80)) = 0.15, \\ D_{\text{Alex}+} &= Dist\,((0.58, 0.57, 0.53), \\ &\quad (0.65, 0.71, 0.80)) = 0.31, \\ D_{\text{Lily}+} &= Dist\,((0.65, 0.42, 0.27), \\ &\quad (0.65, 0.71, 0.80)) = 0.60 \end{aligned} \tag{16}$$

Moreover, we calculate the distance of these three students with *NIS*,

$$\begin{aligned} D_{\text{John}-} &= Dist\,((0.50, 0.71, 0.80), \\ &\quad (0.50, 0.42, 0.27)) = 0.60, \\ D_{\text{Alex}-} &= Dist\,((0.58, 0.57, 0.53), \\ &\quad (0.50, 0.42, 0.27)) = 0.31, \\ D_{\text{Lily}-} &= Dist\,((0.65, 0.42, 0.27), \\ &\quad (0.50, 0.42, 0.27)) = 0.15 \end{aligned} \tag{17}$$

Then, according to Eq. (11), we can obtain the comprehensive score for each student,

$$\begin{aligned} D_{\text{John}} &= D_{\text{John}-}/(D_{\text{John}+} + D_{\text{John}-}) = 0.80, \\ D_{\text{Alex}} &= D_{\text{Alex}-}/(D_{\text{Alex}+} + D_{\text{Alex}-}) = 0.50, \\ D_{\text{Lily}} &= D_{\text{Lily}-}/(D_{\text{Lily}+} + D_{\text{Lily}-}) = 0.20 \end{aligned} \tag{18}$$

Step 4: Rank all students in descending order

According to the comprehensive scores of three students, i.e., D_{John}, D_{Alex}, and D_{Lily} derived in Eq. (18), we can rank them in descending order, i.e., John > Alex > Lily. Finally, we can return the ranked list to interested users.

5 Further Discussion

(1) Here, our focused examination score evaluation and the ranking problem is essentially a decision-making issue that involves multiple quality dimensions (or

criteria) whose values are often of various types[11–16], such as a real number, integer number, Boolean number, and discrete number. In this paper, to simplify, we only assume that the examination scores are from an integer number.

(2) For the common multi-dimensional decision-making problems, weight is recruited to indicate the different significances of multiple dimensions[17–23]. Here, we assume that the involved multiple dimensions are of the same weight. Nevertheless, we argue that weight can also be easily integrated into the PERR method we are using in this study.

(3) Privacy has become an increasingly contested concept. While there is a variety of different private information available; in this paper, we take the historical data generated in past examinations as a kind of user privacy, which are like private data at work in Refs. [24–26].

(4) To simplify, we only discuss the student-course score matrix which is dense enough. We acknowledge that data sparsity is an inherent challenge in common big data applications[27–30].

6 Conclusion and Future Work

Mothers are often eager to know the concrete examination scores of their children at school. However, most schools or teachers have now been now forbidden to release sensitive student examination scores to the public due to privacy concerns, which has made it infeasible for mothers to know the real study level or examination performance of their children. Therefore, a conflict has come to exist between teachers and mothers, which harms the general growing up of students in their study. In critical view of this challenge, a PERR ranking method was proposed in this paper to balance the teachers' privacy disclosure concerns and the mothers' concerns over examination performance. Through a relevant case study, finally, we proved the effectiveness of the proposed PERR method in evaluating and ranking students according to their examination scores while securing sensitive student information at the same time.

Weight seems to be a crucial factor in multi-dimensional decision-making problems. Therefore, in our future academic research, we will aim to further improve the proposed PERR method by considering the weights of different dimensions to enlarge the application scope of PERR. In addition, we will continue to investigate the possibility of integrating our privacy-aware PERR solution with other classical privacy-preservation techniques, such as blockchain[31–33], differential privacy[34, 35], anonymization[36], and program code analyses[37, 38]. Moreover, computation offloading is often necessary, especially in a big data environment[39–45]. Following this, it is expected that more time-efficient and energy-saving versions of PERR are to remain increasingly relevant in future academic research.

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