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AN INFORMATION THEORY-BASED APPROACH FOR DETECTING SPECIAL LECTURERS

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Abstract. *The faculty evaluation forms can be considered as valuable data source to exploit knowledge that helps to improve the quality of teaching and learning in universities. In this paper, we analyze previous studies on exploiting faculty evaluation forms and outlier detection task in data mining. On that basis, we propose and solve the problem of detecting special lecturers assessed considerably differently from the remainder using an efficient information theory-based algorithm. The data are collected from the online faculty evaluation system of our university, with more than 140,000 evaluation forms. Experimental results show that our solution is both effective and efficient. It is remarkably faster than the fast greedy information theory-based algorithm while their accuracies are competitive with each other.*
Keywords: Faculty performance, Teaching performance evaluation, Faculty evaluation form, Outlier detection, Information theory, Entropy

1. **Introduction.** In the context of knowledge economy, the quality of education can be considered competitive advantage of each country. Universities must constantly improve the quality of teaching and learning to provide people with sufficient knowledge to join the labor market and enhance their prestige. Faculty evaluation forms are often collected at the end of each course to improve teaching and learning quality, and support administrators in making decisions. Lecturers realize their strengths and weaknesses according to students' points of view. Students can choose appropriate lecturers. Administrators decide to increase salary or assign tasks to specific lecturers.

Outlier detection is the identification of objects that are considerably different from the remaining data. It is an important task in data mining with many applications in intrusion detection, fraud detection and fault detection. Techniques for outlier detection can be classified into seven approaches [2]: classification-based, clustering-based, nearest neighbor-based, statistical, information theory-based, spectral decomposition-based, and visualization-based. Among these approaches, information theory-based approach has a solid foundation as it is based on mathematics and yields promising results recently.

In this paper, we propose a new problem that exploits faculty evaluation forms to detect special lecturers who are assessed remarkably differently from the remaining ones and suggest using the efficient information theory-based method in [14] to solve that problem. We apply the proposed solution on a real data set with 143,117 forms collected from the online faculty evaluation system of Ton Duc Thang University. The results obtained are compared to the fast greedy information theory-based algorithm for outlier detection in [13].

The main contributions of our work are the following.

- Propose outlier detection problem in exploiting faculty evaluation forms and the solution to tackle that problem.

- Do the experiments on the real data set collected from the online faculty evaluation system of Ton Duc Thang University with more than 143,000 forms.
- Compare to the fast greedy algorithm for outlier detection and discuss obtained results.

The rest of the paper is organized as follows. Section 2 presents the related works on exploiting faculty evaluation forms and detecting outliers. Section 3 proposes the problem of detecting special lecturers and our solution. Section 4 presents the experiments, results obtained and discussion. Section 5 draws the conclusion.

2. Related Works.

2.1. Exploiting faculty evaluation forms. To the best of our knowledge, there are a few studies on exploiting faculty evaluation forms to improve teaching and learning quality, and support stakeholders in making decisions [15]. In terms of the main problems solved, they are divided into three groups: identifying determining factors of faculty performance [1,3,5,7,8,12,16,17], finding the relationship among evaluation factors [11], and adjusting faculty performance based on clustering evaluation forms [6,10,18]. In terms of problem-solving methods, they can be divided into three groups: using statistical methods, using machine learning methods, and combining both statistical methods and machine learning methods.

Recently, Pearson correlation and multiple regression method were used in [20], and structural equation modelling was used in [21] to identify determining factors of students' satisfaction.

2.2. Detecting outliers. Outlier is defined by [4] as follows: "An outlier in a dataset is an observation that deviates so much from other observations as to arouse suspicion that it is generated from a different mechanism". In [2], approaches for outlier detection consist of seven groups: classification-based, clustering-based, nearest neighbor-based, statistical, information theory-based, spectral decomposition-based, and visualization-based.

Among these approaches, information theory-based approach has a solid foundation as it is based on mathematics and yields promising results. According to the authors in [9], outlier detection was considered to be an optimization problem. A local-search heuristics algorithm was proposed to find top-k outliers. Firstly, k objects were selected randomly from the database. Then, each object in the database was considered to replace the most inappropriate object in current k outliers to obtain the minimum entropy of remaining objects in the database. This algorithm was improved by a fast greedy one in [13], in which each time one object was extracted from the database so that the entropy of the remainder is minimal until getting enough k outliers. Another fast greedy algorithm was proposed in [22] consisting of three steps. Firstly, data were divided into clusters and objects in small clusters were kept for the next step. Sum-entropy of each object was then calculated to specify outliers. Finally, attribute value frequency algorithm was used to improve obtained results in the previous step. A simple and effective algorithm was suggested in [14]. The authors proposed a method to calculate the outlier measure of objects, combining the density of each attribute and the importance of that attribute. The importance of an attribute was calculated by complementary entropy with the idea that the more different values the attribute has, the more distinctive it is and the more distinctive the attribute is, and the more important it is. This method also combined the last two steps proposed in [22] in an outlier measure. The experimental results obtained by this algorithm show its effectiveness and efficiency in detecting outliers.

3. **Problem and Solution.**

3.1. **Problem definition.** In general, the exploitation of useful knowledge from evaluation forms is still limited as aforementioned.

On the other hand, outlier detection is an important task in data mining with many applications, especially in detecting anomalies in a system. Therefore, we propose the problem of detecting special lecturers who are assessed considerably differently from the remainder. On that basis, we can conduct deeper analysis of the characteristics of these lecturers such as age, and qualifications, the relationship of these lecturers with the lecturers having extremely high or low overall ratings, and other analysis to grasp the human resource in our university. Then we suggest using the efficient information theory-based method in [14] to solve that problem. We select this method as its high accuracy and fast run time. Although it is originally used for categorical data, it is reasonable and simple to convert our data from number score to letter grade.

Let $F_{ijkl} =< f^1_{ijkl}, f^2_{ijkl}, \ldots, f^n_{ijkl} >$ be an evaluation form of student i about lecturer j, after studying course k in semester l, in which f^m_{ijkl} is the mth factor of the form and $domain(f^m_{ijkl}) = \{1, 2, 3, 4, 5\}$, equivalent to a Likert-scale with intervals of 1 to 5 (5 = Strongly satisfied, 4 = Satisfied, 3 = Neither, 2 = Dissatisfied, 1 = Strongly Dissatisfied). The form consists of n questions or n evaluation factors, in which first $n-1$ factors are specific factors while the last factor is the overall rating. A database D contains a set of all evaluation forms.

Let $T_{jl} =< t^1_{jl}, t^2_{jl}, \ldots, t^n_{jl} >$ be average rating of lecturer j in semester l, in which t^m_{jl} is the average rating of the mth factor. This feature vector describes specialized features of each lecturer based on all of the evaluation forms about him/her.

Let $I(j, l)$ be a set of students taught by lecturer j in semester l, and $K(j, l)$ be the set of courses taught by lecturer j in semester l.

According to [14], let A^m be the mth factor, and U be the set of average ratings of all lecturers in all semesters. Definitions and formulas applied for exploiting evaluation forms are as follows.

The binary relation on the factor A^m between average ratings of lecturers:

$$Bin(A^m) = \{(x, y) \in UxU | x.A^m = y.A^m\}$$

The equivalence class on the factor A^m determined by average rating of lecturer x:

$$[x]^m_A = \{y \in U | (x, y) \in Bin(A^m)\}$$

The partition of U on the factor A^m:

$$Par(A^m) = \{[x]^m_A | x \in U\} \tag{1}$$

Assume that $Par(A^m) = \{X_1, X_2, \ldots, X_p\}$. The complementary entropy of the factor A^m:

$$E(A^m) = \sum_{i=1}^{p} \frac{|Xi|}{|U|} \left(1 - \frac{|Xi|}{|U|}\right), \tag{2}$$

in which $|X|$ represents the number of items in X.

The weight of the factor A^m:

$$W(A^m) = \frac{1 - E(A^m)}{\sum_{i=1}^{n} (1 - E(A^m))}$$

The density of the factor A^m for average rating of lecturer x:

$$Den_x(A^m) = \frac{|[x]_{A^m}|}{|U|} \tag{3}$$

The weighted density for average rating of lecturer x:

$$WDen_x = \sum_{i=1}^{n} Den_x\left(A^m\right).W\left(A^m\right) \tag{4}$$

3.2. **Solution.** Our solution is a 3-stage process as follows:

- Stage 1 – Pre-process data:
  - Step 1.1: Firstly, we eliminated inconsistent evaluation forms with the deviation between average rating of specific factors and overall rating being greater than δ because the reason for the lack of consistence may be that the students did not pay attention to the content of the questions completely and seriously.
  - Step 1.2: We then calculated the feature vectors of all lecturers.
  - Step 1.3: We converted feature vectors from number score to letter grade as follows: 5→‘A’, 4→‘B’, 3→‘C’, 2→‘D’, 1→‘E’.

The pseudo code of this stage:

Step 1.1: Eliminate all inconsistent evaluation forms
for $l = 1$ **to** *number of semesters* **do**
for $j = 1$ **to** *number of lecturers* **do**
for $i \in I(j,l)$ **do**
for $k \in K(j,l)$ **do**
//calculate the sum of rating of student i for lecturer j after
studying course k in semester l
$sum(i,j,k,l) = 0$
for $m = 1$ **to** $n-1$ **do**
$sum(i,j,k,l) = sum(i,j,k,l) + f_{ijkl}^{m}$
end for
$avg(i,j,k,l) = sum(i,j,k,l)/(n-1)$
if $(\lvert avg(i,j,k,l) - f_{ijkl}^{n}\rvert >= \delta)$ **then**
exclude F_{ijkl} from D
end if
end for
end for
end for
end for

Step 1.2: Calculate feature vectors
for $l = 1$ **to** *number of semesters* **do**
for $j = 1$ **to** *number of lecturers* **do**
for $m = 1$ **to** n **do**
//calculate the sum of rating for lecturer j in semester l
in terms of mth factor
$acc\_sum(j,l,m) = 0$
$acc\_count(j,l,m) = 0$
for $i \in I(j,l)$ **do**
for $k \in K(j,l)$ **do**
$acc\_sum(j,l,m) = acc\_sum(j,l,m) + f_{ijkl}^{m}$
$acc\_count(j,l,m) = acc\_count(j,l,m) + 1$
end for
end for
$t_{jl}^{m} = round(acc\_sum(j,l,m)/acc\_count(j,l,m))$
end for
end for
end for

- Stage 2 – Detect outliers:

Stage 2: Weighted density-based outlier detection algorithm [14]
for $m = 1$ **to** n **do**
//calculate $Par(A^m)$ according to (1)
//calculate $E(A^m)$ according to (2)
end for
for $x = 1$ **to** *number of semesters* number of lecturers* **do**
for $m = 1$ **to** n **do**
//calculate $Den_x(A^m)$ according to (3)
end for
//calculate $WDen_x$ according to (4)
end for
//sort records x by ascending order of $WDen_x$

- Stage 3 – Post-process data: We analyzed results obtained from Stage 2 and drew conclusions.

4. Experiments and Results.

4.1. Dataset. We collected data from the online faculty evaluation system of Ton Duc Thang University for the second semester 2014-2015. The total number of evaluation forms obtained is 143,117. The form consists of 13 closed questions (12 specific questions and a question about overall satisfaction) and 2 open questions.

For closed questions, we use the Likert scale as mentioned before. The specific evaluation factors were divided into 12 specific questions corresponding to detailed evaluation factors about the lecturers. Thus, each evaluation form can be considered as a student's perspective on specialized features or the strengths and the weaknesses of a lecturer.

4.2. Experiments and measurements. In the pre-processing stage, we eliminated the evaluation forms with the deviation between the average rating of 12 specific factors and overall satisfaction being greater than one ($\delta = 1$). The number of remaining forms after this stage is 139,994 (97.82%). The value of each faculty evaluation factor is the average of corresponding factor from all relevant forms, rounded to the unit. The results obtained are 647 12-dimensional vectors describing specialized features of 647 lecturers of the whole university.

To assess our solution, we implemented it (namely Simple) and replaced the algorithm in [14] by the algorithm in [13] (namely Greedy), which is an improved version of original information theory-based outlier detection algorithm in [9] in terms of time efficiency for Stage 2. All experiments were conducted on a Lenovo y510p Intel(R) Core(TM) i7-4700MQ CPU @ 2.40GHz (8 CPUs), ~2.4GHz, 16GB RAM, Window 10, using Matlab R2016a programming language.

We compared two solutions in terms of accuracy and time consumption. In order to test their accuracy in detecting outliers, we used the method proposed in [19], in which the higher the percentage of outliers belonging to rare classes is, the higher the accuracy of that method is.

After pre-processing stage, we obtained 647 records representing 647 lecturers. According to overall ratings, these records can be divided into three classes, namely high class (overall ratings = 5, with 15 out of 647 records or 2.3%), average class (overall ratings = 4, with 607 out of 647 records or 93.8%), low class (overall ratings = 3, with 25 out of 647 records or 3.9%). As we did not have an absolutely accurate faculty performance evaluation to test the results, we considered using high class and low class as rare classes which contain special lecturers and using idea in [19] as mentioned before. We obtained 40 rare objects in these two classes.

4.3. **Results and discussion.** Comparable results on our data set between Simple and Greedy with regard to run time and accuracy are presented in Table 1 and Table 2, respectively.

Table 1. Run time of two solutions

Solution	Run time (second)	Speedup
Simple	0.815855648	506
Greedy	412.7214	

Table 2. Accuracy in detecting outliers of two solutions

Top ratio (number of objects)	**Number of rare classes included (Coverage)**	
	Simple	Greedy
1% (7)	7 (18%)	7 (18%)
2% (13)	13 (33%)	13 (33%)
4% (26)	26 (65%)	26 (65%)
6% (39)	37 (93%)	39 (97.5%)
8% (52)	40 (100%)	40 (100%)
10% (65)	40 (100%)	40 (100%)

It can be seen from the result in Table 1 that with regard to run time, our solution is remarkably faster than Greedy solution (506 times). In order to validate this experimental result, we analyzed the complexity of two algorithms on Stage 2. From the pseudo-code in Section 3, the Stage 2 in our solution has time complexity $O(s*l*f)$, with s being the number of semesters, l being the number of lecturers, and f being the number of factors. On the other hand, Greedy solution used in Stage 2 has time complexity $O(s*l*f*k*p)$, with k being the number of outliers and p being the number of distinct values of each factor (assumed equally). Therefore, the proposed method is more efficient and suitable for mining large dataset, which is very important in data mining applications in reality.

In terms of accuracy in detecting outliers in Table 2, in 5 out of 6 cases, the accuracies of two solutions are the same. Both of them obtain the maximum coverage for those cases, which means that all of the detected outliers belong to rare classes when the number of objects is less than 40 in the first three cases, and all the rare objects are detected when the number of objects is more than 40 in the last two cases. This can prove their high accuracies. They only differ in one case in which the top ratio equals 6%. In this case, there are two outliers detected in our solution which do not belong to rare classes. We examined these outliers in their original forms, which are presented as two 12-dimensional vectors as follows:

$$O1 = < 3, 3, 4, 4, 3, 3, 3, 4, 4, 3, 4, 4, 4 >$$

$$O2 = < 4, 3, 4, 4, 4, 3, 3, 3, 3, 3, 4, 4, 4 >$$

It shows that a half of their factors are assessed 3 out of 5, which is rare score. It is reasonable to consider them as outliers in reality. However, as their overall ratings are 4 out of 5 (overall ratings are rounded to the unit), they are not considered rare classes which only include 3 and 5 values for overall ratings.

5. **Conclusion and Future Works.** In this paper, we analyzed the previous studies on exploiting faculty evaluation forms and the importance of outlier detection task in data mining. On that basis, we proposed a new problem that exploits faculty evaluation forms to detect special lecturers assessed considerably differently from the remainder and suggested the solution to solve the problem using the information theory-based method in

[14]. We applied the solution in analyzing real data collected from the online evaluation system of Ton Duc Thang University and compared results with the fast greedy information algorithm in [13]. Experimental results show that two algorithms are competitive in accuracy while our solution is much faster in run time that makes it suitable for mining large dataset.

In future, we continue to conduct deeper analysis of the characteristics of special lecturers. In addition, we will also investigate the change of assessment trend over time as well as mining knowledge from open questions in the evaluation forms.

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