A Data Mining-Based Approach for Exploiting the Characteristics of University Lecturers

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Abstract. The faculty evaluation forms can be considered as valuable data source to exploit knowledge which helps to improve the quality of teaching and learning in universities. In this paper, we analyze previous studies on exploiting faculty evaluation forms according to major problems and their solutions. On that basis, we propose and solve the problem of mining useful knowledge about human resource of Ton Duc Thang University using a data mining-based approach. The experimental data are collected from the online faculty evaluation system of our university, with more than 140,000 evaluation forms. We apply the solution to analyze the data set and draw meaningful comments for the characteristics of the lecturers so that human resource can be exploited and constructed appropriately and efficiently. The results obtained are compared to a previous study on clustering lecturers based on performance and correlation coefficient analysis method.

Keywords: Student feedback · Faculty performance · Teaching performance evaluation · Faculty evaluation form · Clustering

1 Introduction

The quality of education has always been considered as the foundation of the long-term development of all countries. In order to provide people with sufficient knowledge and skills to labor market and enhance their reputation, universities must constantly improve the quality of teaching and learning. Many strategies have been applied to measure the faculty performance, including: student ratings, peer ratings, self-evaluation, videos, student interviews, exit and alumni ratings, employer ratings, administrator ratings, teaching scholarships, teaching awards, learning outcome measures and teaching portfolio [2]. Among these strategies, student ratings are considered as the most popular evaluation tool [4].

In this paper, based on the analysis of previous studies on the exploitation of knowledge from faculty evaluation forms to improve the quality of teaching and support stakeholders such as administrators, lecturers and students in making decisions, we propose a new problem that exploits evaluation forms to obtain useful knowledge about human resource of our university and the method to solve that problem. On that basis, administrators can make decisions in salary increase and task assignment; students can choose appropriate lecturers; lecturers realize their strengths and weaknesses.

P. Perner (Ed.): ICDM 2016, LNAI 9728, pp. 41–53, 2016.
DOI: 10.1007/978-3-319-41561-1_4

We apply the proposed solution on a real data set including 143,117 forms from the online faculty evaluation system of Ton Duc Thang University. The results obtained are compared to the only study on clustering lecturers based on performance and correlation coefficient analysis method. It provides an overview of human resource in our university, laying the foundation for the exploitation and development of human resource efficiently.

The main contributions of our work are the following:

- Construct a new faculty evaluation form suitable for our university
- Analyze previous studies in terms of main problems solved
- Propose a new problem and the solution to tackle that problem
- Apply the solution to analyze the data set collected from the online faculty evaluation system of Ton Duc Thang University and discuss about results obtained
- Compare the results obtained to the only study on clustering lecturers based on performance and correlation coefficient analysis method

The rest of the paper is organized as follows. Section 2 presents the studies of exploiting faculty evaluation forms in terms of solved problem and proposed method. Section 3 proposes new problem and its solution. Section 4 presents the experiments and results obtained. Section 5 is used for a discussion. Section 6 draws the conclusion.

2 Related Works

To the best of our knowledge, there are a few studies on exploiting faculty evaluation forms to improve teaching quality and support stakeholders in making decisions. This section is divided into three parts according to the main problems solved [15].

2.1 Identifying Determining Factors of Faculty Performance

Regression analysis was applied to find the relationship between one dependent variable, which was the faculty performance in this case, and one or more independent variables such as subject knowledge, communication skills, etc. In [12], the authors analyzed the 4,589 evaluation forms about an online MBA program of a university in 2007 to identify determining factors of faculty performance and course satisfaction. Each form consists of many questions divided into three groups of criteria: personal attributes, learner facilitation and quality of feedback. Two overall evaluation factors are overall performance of the lecturer and overall satisfaction of the course. The result obtained shows that personal attributes are determining factors. In [1], evaluation forms were collected from Management Information System department's courses at Bogazici University between 2004 and 2009 and some other lecturer and course characteristics drawn from the Student Evaluation of Teaching research (SET). Stepwise regression method was used to identify the determining factors of faculty performance. The experimental results show that five factors consisting of the attitudes of the lecturer, the attendance of the student, the ratio of students filled the questionnaire to the class size, the lecturer is a part-time laborer and the workload of the course largely determine the faculty performance.

Statistical tests such as Chi-square test, Info Gain test, Gain Ratio test were used to analyze the impact of each factor on faculty performance. In [7], the empirical data are the faculty evaluation forms from the graduates of a faculty at an engineering university in 3 years. The evaluation factors include: teacher name, speed of delivery, content arrangement, presentation, communication, knowledge, content delivery, explanation power, doubts clearing, discussion of problems, overall completion of course and regularity, students attendance, and result. The result is that content arrangement is the determining factor of faculty performance.

Apriori algorithm was used to find the association rule with the form $A \rightarrow B$ in which A was evaluation factor and B was faculty performance. In [8], the empirical data were collected from a faculty evaluation system in spring semester of 2007–2008. The experimental result shows that the teaching content and teaching attitude have the strongest relationship with the faculty performance. In [3], the authors collected data from a personnel management system and educational evaluation system. Apriori algorithm was used to find the relationship between the personal information of lecturers namely gender, age, certification and overall rating; the relationship between the evaluation factors namely teaching attitude, teaching ability, teaching content, teaching organization, teaching methods and faculty performance. The factors having strong relationship with the faculty performance should be focused to improve the quality of teaching.

Some algorithms were applied to build the model to classify faculty performance based on evaluation factors. In [5], the empirical data were collected from the evaluation forms of an online system based on four groups of factors: subject knowledge, teaching skills and assessment methods, behavior towards students, communication skills. Models for classifying faculty performance using those factors obtained from M5P [18] and REP [19] algorithms were used to identify the determining factors of faculty performance. In particular, the factor at the root of the tree is the determining factor because it helps to split the data into groups with the lowest entropy. The lower level in the tree the factor appears at, the less impact on the faculty performance it has. REP algorithm builds the tree faster and achieves higher accuracy than M5P algorithm in the data set. Subject knowledge is the determining factor of faculty performance in both algorithms. In [1], two CHAID and CART algorithms were used to identify the determining factors of faculty performance. Experimental results generated two different trees. Factors appearing at all levels in the tree are considered as the set of the important factors to faculty performance, in which the attitudes of the lecturer at the root of both trees is the most important factor. In [7], the empirical data were collected from the graduates of a faculty at an engineering university in 3 years. Classification methods consisting of four algorithms: Naive Bayes, ID3, CART, LAD tree were used to build faculty performance classification model based on evaluation factors. These factors include: teacher name, speed of delivery, content arrangement, presentation, communication, knowledge, content delivery, explanation power, doubts clearing, discussion of problems, overall completion of course and regularity, students attendance, and result. The result obtained shows that Naïve Bayes algorithm has the highest accuracy.

2.2 Finding the Relationship Among Evaluation Factors

Apriori algorithm was used to find the relationship among the evaluation factors in [11], including: subject knowledge, teaching with new aids, motivating self and students, communication skills, class control, punctuality and regularity, knowledge beyond syllabus, and aggregate.

2.3 Adjusting Faculty Performance Based on Clustering Evaluation Forms

Some algorithms were applied to cluster evaluation forms then recalculate the faculty performance based on clusters obtained. In [6], the evaluation factors consist of clear and understandable presentation, methodical and systematic approach, tempo of lecturers, preparedness for a lecture, the accuracy of arrival to the lecture, encouraging students to participate in classes, informing students about their work, considering student comments and answering questions, availability (through individual teacher/student meetings or via e-mail). The authors partitioned students into several clusters based on the similarity on evaluation forms using *k*-means algorithm then analyzed the faculty performance in each cluster. In [10], the empirical data obtained from the 3,000 student feedbacks about 77 factors to assess 50 Information Technology lecturers of a university. Expectation Maximization algorithm [20] was used to cluster data according to four levels of performance evaluation: very good, good, satisfactory and poor. The number of clusters is 14. The average value of faculty performance was calculated for each aforementioned level based on results obtained from the clusters.

3 Problem and Solution

3.1 Problem Definition

In terms of the main problems solved as described in the previous section, the studies are divided into three groups: identifying determining factors of faculty performance, finding the relationship among evaluation factors, and adjusting faculty performance based on clustering evaluation forms. In terms of problem-solving methods, the studies on exploiting knowledge from faculty evaluation forms can be divided into three groups: using statistical methods, using machine learning methods, and combining both statistical methods and machine learning methods. While statistical methods are suitable for identifying important factors that influence faculty performance, using machine learning methods in finding relationship among evaluation factors are relevant. However, in general, the exploitation of useful knowledge from evaluation forms is still limited. Therefore we propose the problem of exploiting faculty evaluation forms to obtain characteristics of the human resource in our university.

Let $F_{ijkl} = \ <f_{ijkl}^1, f_{ijkl}^2, \ldots, f_{ijkl}^n>$ be an evaluation form of student *i* about lecturer *j*, after studying course *k* in semester *l*, in which f_{ijkl}^m is the m^{th} factor of the form and *domain*(f_{ijkl}^m) = {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 $T_{jl} = \ <t_{jl}^1, t_{jl}^2, \ldots, t_{jl}^n>$ be average rating of lecturer j in semester l, in which t_{jl}^m is the average rating of the m^{th} 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, $K(j,l)$ be the set of courses taught by lecturer j in semester l.

3.2 Method

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.

The pseudo code of the stage 1 is as follows:

```
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 ∈ I(j,l) do
             for k ∈ 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 (|avg(i,j,k,l)- f_ijkl^n| >= δ) 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 m^th factor
             acc_sum(j,l,m) = 0
             acc_count(j,l,m) = 0
             for i ∈ I(j,l) do
                for k ∈ 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 = acc_sum(j,l,m) / acc_count(j,l,m)
          end for
       end for
    end for
```

- Stage 2 - Process data: We divided lecturers into different clusters according to the similarity of the feature vectors using k-means [17] and X-means [13] methods. We chose *k*-means as it is the most common clustering algorithm. With each *k*, we calculated the sum of the squared error measure (SSE) [16] to find the most suitable value of *k*:

$$SSE = \sum_{i=1}^{K} \sum_{x \in C_i} dist^2(m_i, x)$$

  – x is a vector which belongs to cluster C_i
  – m_i is a representative vector for cluster C_i (the mean of all vectors in cluster C_i)
  – *dist* is Euclidean distance between each vector and representative vector

  We also chose *X*-means algorithm which is extended from *k*-means and able to estimate the optimal number of clusters and more efficient in terms of computational cost than traditional *k*-means algorithm.
- Stage 3 - Post-process data: We analyzed results obtained from stage 2 and drew conclusions.

3.3 Comparison

To the best of our knowledge, there is one study on clustering lecturers based on performance. In [9], the authors identified 77 factors which influence faculty performance. The empirical data include information about 50 Information Technology lecturers of a university. These lecturers were clustered according to performance, using k-means algorithm. The result shows that there are two clusters: cluster 1 consists of the lecturers assessed distinctively while cluster 2 consists of the lecturers who are similar to the others. We implemented this method with our data and then compared results obtained with those of our method.

4 Experiments and Results

We have 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 two open questions. The form was constructed on the following basis:

- SEEQ evaluation form consists of 33 closed questions and one open question [14] which is widely used in the world
- Evaluation form of the first semester 2014–2015 in our university
- Evaluation form of the second semester 2013–2014 in our university
- Suggestion from departments in our university
- Characteristics of Vietnamese students and our university's students
- Requirements and current situation of our university

For closed questions, we use the Likert scale as mentioned before. The specific evaluation factors were divided into 12 specific questions as presented in Table 1. Specific questions or specific factors in the faculty evaluation form, 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.

Table 1. Specific questions or specific factors in the faculty evaluation form

ID	Question
Q1	Are you satisfied with the specialised knowledge/skills of the lecturers
Q2	Lecturers can inspire students
Q3	Are you satisfied with the enthusiasm of the lecturers
Q4	Lecturers often discuss and answer the questions of students
Q5	Lecturers prepare complete and updated course materials
Q6	Lively, clear, easy to understand and take notes lectures
Q7	Lecturers encourage students to give questions, situations, new issues and discuss in class
Q8	Lecturer present and discuss about the development trends and applications of the subject
Q9	Individual assignments and group assignments are given to help students grasp the subject
Q10	Lecturers instruct students the methods of self-study and deeply exploiting the subject
Q11	Lecturers clearly present the forms of examination and assessment to students
Q12	Contents of the lectures are suitable for the tests

In the preprocessing 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 nearest unit. The results obtained are 647 12-dimensional vectors describing specialized features of 647 lecturers of the whole university.

We applied *X*-means algorithm for clustering the vectors. The number of clusters obtained is 4. The number of members in each cluster and the values of cluster centroid are presented in Tables 2 and 3, respectively.

Figure 1 illustrates the values of cluster centroid on the graph.

Table 2. Number of members in each clusters

Cluster	Number of members
1	54
2	507
3	28
4	58

Table 3. Values of cluster centroid

Attribute	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Q1	4.777778	4.005906	3.392857	4
Q2	4.351852	3.984252	3	3.052632
Q3	4.981481	4.021654	3.285714	3.982456
Q4	4.796296	4.007874	3.392857	4
Q5	4.333333	4.001969	3.535714	4
Q6	4.277778	3.988189	3	3.017544
Q7	4.055556	3.980315	3.071429	3.789474
Q8	4.037037	3.990157	3.107143	3.824561
Q9	4.037037	3.994094	3.285714	3.789474
Q10	4.037037	3.992126	3	3.614035
Q11	4.407407	4.005906	3.75	4
Q12	4.314815	4.003937	3.571429	3.982456

We used *k*-means algorithm implemented by Rapid-Miner Studio 6.4 and analyzed results from this tool using SSE. Figure 2 illustrates the relationship between the number of clusters *k* and SSE. We chose *k* in the range [2, 17] with 17 being the number of departments in our university. It can be seen from the line graph that the value $k = 4$ creates an elbow, where SSE value starts declining much more slowly. In other words, from the point $k = 4$ the clusters begin to be split into smaller clusters without improving SSE significantly. Therefore the relevant number of clusters is 4.

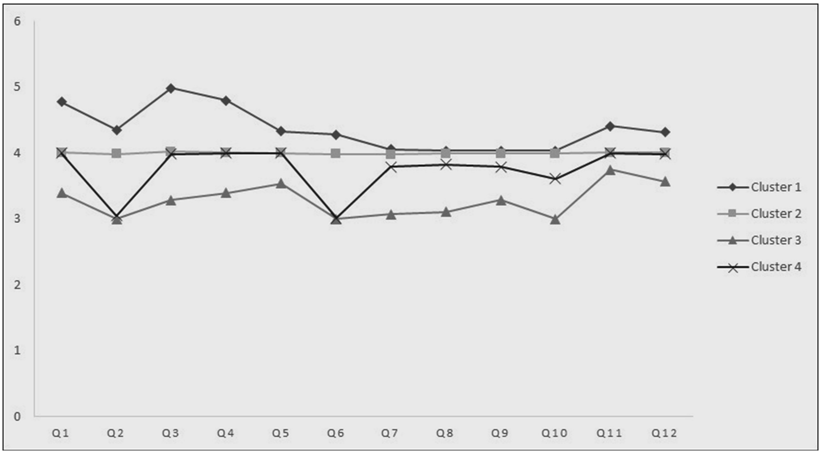

Fig. 1. Centroid of each cluster

In general, the result we obtained with this value matches the result from *X*-means algorithm presented.

We implemented the method in [9] which proposed to cluster lecturers according to their performance by using X-means algorithm. The result shows that lecturers are distributed into two clusters as shown in Fig. 3. We then analyzed each cluster obtained. Cluster 1 (centroid value: 4.248) consists of 385 lecturers with overall rating being greater than or equal to 4, who are in cluster 1 and a part of cluster 2 (with high overall rating) in our method. Cluster 2 (centroid value: 3.728) consists of 262 lecturers with overall rating being less than 4, who are in the remaining part of cluster 2 (with low overall rating), cluster 3 and cluster 4 in our method.

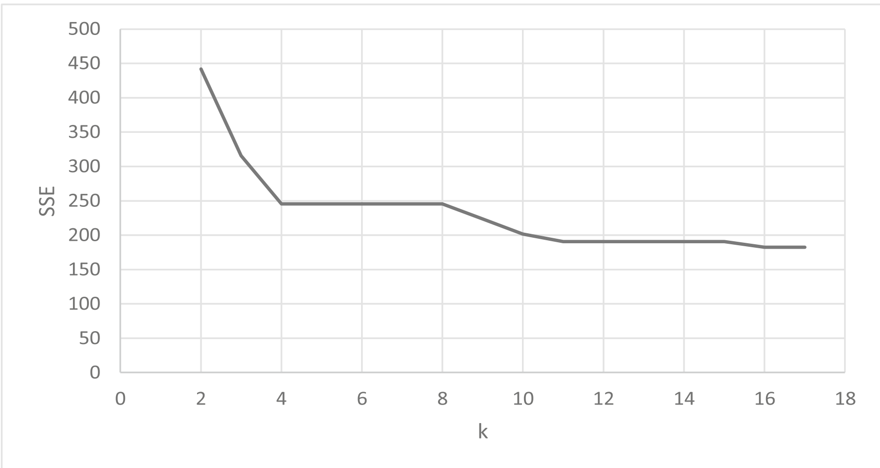

Fig. 2. The relationship between the number of clusters k and SSE measure

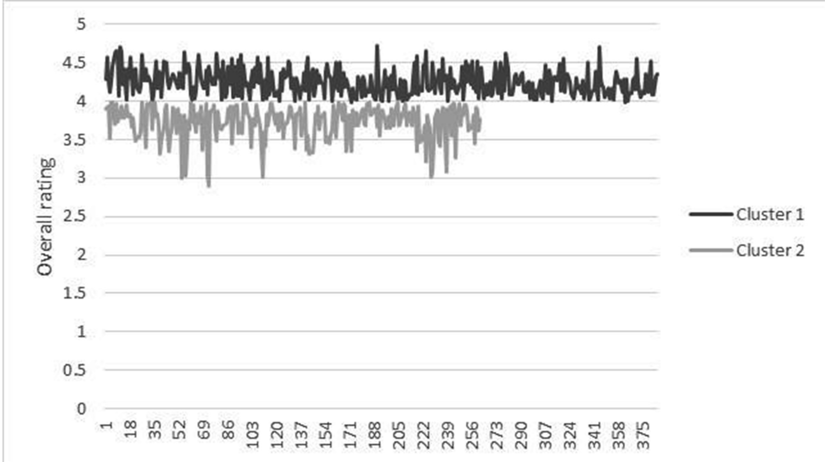

Fig. 3. Lecturers distributed into two clusters according to the method in [9]

In order to examine influence of each evaluation factor on the overall rating in more details, we conducted the analysis about correlations among them. We calculated Pearson correlation by using SPSS software. The result obtained is presented in Table 4.

Table 4. Correlation coefficient between specific factors and overall rating

ID	Correlation coefficient
Q1	0.738
Q2	0.745
Q3	0.728
Q4	0.709
Q5	0.676
Q6	0.745
Q7	0.665
Q8	0.675
Q9	0.685
Q10	0.702
Q11	0.677
Q12	0.709

5 Discussion

From the results of clustering, we drew the following comments about the human resource in our university:

- In general, the lecturers in our university are rated highly. More than 86 % of the lecturers belong to cluster 1 and cluster 2 with the ratings for 12 evaluation factors being greater than or equal to four. The factors getting the highest satisfaction are enthusiasm (Q3, Q4) and knowledge conveyed by the lecturer (Q1). It is quite reasonable for a university that was founded only 18 years ago and the majority of lecturers are young. On the other hand, the ability to inspire students (Q2) and give lively lectures (Q6) is considered as weaknesses of all lecturers. The administrators should pay attention to this problem and try to remedy the situation. In addition, some combinatorial aspects of lecturer characteristics can also be derived from the clustering result. For example, lecturers that are evaluated as not being clear and easy to understand (Q6) are also evaluated as being less able to inspire students (Q2). Another example is that lecturers often discuss and answer the questions of students (Q4) are also evaluated as having good knowledge or skills (Q1).

- Most lecturers belong to cluster 2 (78.4 %) and are assessed uniformly for all criteria (4/5 in Likert scale), showing that there is no significant difference in the quality of teaching among the lecturers in the university.
- Cluster 1 consists of the lecturers with the highest rating (8.3 %). There is no remarkable difference between the lecturers of cluster 1 and that of cluster 2 except evaluation factors Q1, Q3 and Q4 in which Q3, Q4 assess the enthusiasm of the lecturers. More than 97 % (38 out of 39) of the lecturers with the average ratings of the overall satisfaction being equal to 5 belong to cluster 1. Therefore it can be seen that the enthusiasm plays an important role in improving the overall satisfaction. The remaining criteria such as the ability to inspire students (Q2) and give lively lectures (Q6), the expansion of lectures (Q7, Q8), and applications and deeply exploiting the subject (Q9, Q10) are not appreciated compared to the aforementioned criteria. It can be explained by the fact that as the lecturers are young, they do not have much practical experience, wisdom and ability to apply academy knowledge.
- Cluster 3 consisting of 4.3 % of the lecturers is assessed almost similar to the lecturers of cluster 2 except two factors: the ability to inspire (Q2) and give lively lectures (Q6).
- Cluster 4 includes the lecturers with the lowest ratings, accounting for 9 %. These lecturers were rated higher in objective factors such as preparing complete and updated course materials (Q5), presenting clearly the forms of examination and assessment (Q11), contents of the lectures are suitable for the tests (Q12). Therefore, they need to pay attention to improve a variety of factors including specialized knowledge and ability to convey knowledge.

With regards to the method proposed in [9], it is clear that it only partitions lecturers according to overall rating, not based on their specific features. Therefore it can not provide valuable knowledge about characteristics of lecturers belonging to each cluster.

When it comes to the correlation coefficient analysis method, it can be seen that all correlation coefficients are greater than 0.6, which are considered as strong correlations. Among 12 factors, Q2 and Q6 are the factors which have the strongest correlation to the overall rating. These are also the weaknesses of lecturers in our university as analyzed before. The next important factors are Q1 and Q3. The interesting thing is that they are also the strengths of our lecturers. Overall, the results obtained by analyzing the correlation coefficient are consistent to comments drawn from clustering characteristics of the lecturers.

6 Conclusion and Future Works

In this paper, we analyzed the previous studies on exploiting faculty evaluation forms in terms of the main problems solved and their solutions. In general, these studies only focus on solving a few problems such as identifying factors that have the largest influence on faculty performance or seeking dependencies among evaluation factors. On that basis, we proposed a new problem which clusters evaluation forms according to the similarity in specialized features of the lecturers in order to build an overall picture of human resource in our university. We have applied the solution in analyzing real data collected from the online evaluation system of Ton Duc Thang University. We drew useful comments about the strengths and weaknesses of the lecturers in the university as well as those of the lecturers belonging to each cluster, gave some explanations, and identified evaluation factors which influence the overall satisfaction of the students. These results obtained after comparing to applying correlation coefficient analysis. We also compared results obtained to those of the previous study on clustering lecturers and proved that our method provides more valuable information about the characteristics of lecturers.

In future, we continue to exploit the data source to predict the faculty performance based on personal characteristics of the lecturers such as qualifications, age, gender, etc. 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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