

# Cluster Analysis of the Competency of Engineering Teachers

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**Keywords:** Cluster analysis; Evaluation of competency; Engineering teachers

**Abstract.** On the basis of introduction of cluster analysis, analytic hierarchy process (AHP for abbreviation) is applied to evaluate the competency of engineering teachers in W university. Then cluster analysis is made by the use of statistical software SPSS19 .0 to evaluate the sample engineering teachers from their self-assessment competency questionnaires in accordance with K-means method. From the results of cluster analysis, it is found that the results is approximately the same with the results of AHP with the advantage of broader inclusion, showing that the cluster analysis can more scientifically classify the competency of engineering teachers and provide basis for decision making in universities as well.

## Introduction

In the field of socio-economy, there are a great number of problems of classifications and classification structure models. Thus cluster analysis is a useful method of classification of individuals or objects to make similarities stronger within the same types than that within other types[1-2]. The aim of cluster analysis is to maximize homogeneity as well as the heterogeneity among the same class of objects[3-4].

Previous studies mainly rely on the experience and expertise to deal with qualitative classifications, resulting in many subjective or arbitrary classifications which are not good reminders to reveal the inherent nature of the differences and links of objective things. As for multi-factor or multi-index classifications, qualitative classifications are more difficult to achieve accuracy. In order to overcome the shortcomings of the qualitative classifications, mathematics is gradually introduced into the taxonomy to form the numerical taxonomy. And with the introduction of multivariate analysis, cluster analysis is used to classify cases or variables later [5-6].

## Competency Evaluation of Engineering Teachers by Means of AHP

According to the requirements of full-time engineering teachers in universities, performance evaluation of engineering teachers are designed to include four guideline layers of quality, knowledge, teaching and research capability and personal feature[7-9]. What's more, these four guideline layers include 24 different indexes to constitute the index layers so as to form a complete performance evaluation system of engineering teachers. For the four guideline elements, pairwise comparison judgment matrix  $(U_{ij})_{4 \times 4}$  can be obtained and judgment matrix is indicated in the form of Table 1. Among them, the  $U_{ij}$  represents the importance of  $U_i$  and  $U_j$  which are compared with target value. By means of 1-9 scale method proposed by Satty, the importance of indicators is scale-divided[10]. Apart from that, weighting of indicators are judged by experts according to their backgrounds and experiences. The scale and the results of relative importance of index are obtained from averaging correction, judgment matrix is established. After calculation, judgment matrix has passed consistency test, the results are shown in Table 1.

Table 1 Performance target—index layer judgment matrix of engineering teachers in universities

U	$U_1$	$U_2$	$U_3$	$U_4$
$U_1$	$U_{11}$	$U_{12}$	$U_{13}$	$U_{14}$
$U_2$	$U_{21}$	$U_{22}$	$U_{23}$	$U_{24}$
$U_3$	$U_{31}$	$U_{32}$	$U_{33}$	$U_{34}$
$U_4$	$U_{41}$	$U_{42}$	$U_{43}$	$U_{44}$

Table 2 calculation results of consistency check

	CR	$\lambda_{\max}$	CI	RI
target U—guideline $U_i$	0.0115	4.0310	0.0103	0.9
quality $U_1$ —index layer	0.0031	7.0247	0.0041	1.32
knowledge $U_2$ —index layer	0.0032	3.0037	0.0018	0.58
teaching and research capabilities $U_3$ —index layer	0.0559	7.4431	0.0739	1.32
personal features $U_4$ —index layer	0.0026	7.0203	0.0034	1.32

$AW = \lambda_{\max} W$  is used to solve  $\lambda_{\max}$  corresponding feature vector  $W$  of  $\lambda_{\max}$ , which is normalized, namely the weighting coefficient of the corresponding index of the same level for some indicator of the top level. Root method is used, calculating method are seen in formula (1-1), formula (1-2) and (1-3). The results are in table 3.

(1) To calculate the product  $M_i$  of the elements of each row of judgment matrix

$$M_i = \prod_{j=1}^n a_{ij} \quad (i=1,2,\dots,n) \quad (1-1)$$

(2) To calculate n-th root  $\bar{W}_i$  of  $\bar{W}_i$

$$\bar{W}_i = \sqrt[n]{M_i} \quad (1-2)$$

(3) To normalize the vector  $\bar{W} = \bar{W}_1, \bar{W}_2, \dots, \bar{W}_n^T$

$$W_i = \bar{W}_i / \sum_{j=1}^n \bar{W}_j \quad (1-3)$$

Therefore,  $W = W_1, W_2, \dots, W_n^T$  is the feature vector of seeking weight.

Table 3 Total weight of each element

	first level	weight $W_i$	second level	stratification weight	total weight $W_{ij}$
U	quality $U_1$	0.2776	spirit of dedication $U_{11}$	0.0729	0.0202
			benevolent acceptance $U_{12}$	0.0706	0.0196
			integrity $U_{13}$	0.2151	0.0597
			social responsibility $U_{14}$	0.1320	0.0366
			student orientation $U_{15}$	0.0706	0.0196
			spread of positive energy $U_{16}$	0.0688	0.0191
			role model $U_{17}$	0.3699	0.1027
	knowledge $U_2$	0.4668	professional expertise $U_{21}$	0.3090	0.1442
			research method $U_{22}$	0.5816	0.2715
			engineering practice $U_{23}$	0.1095	0.0511
	Teaching and scientific research capability $U_3$	0.1603	study apperception $U_{31}$	0.0442	0.0071
			teamwork $U_{32}$	0.2139	0.0343
			theory with practice $U_{33}$	0.1251	0.0201
			organization of teaching $U_{34}$	0.0592	0.0095
			innovation and exploration $U_{35}$	0.1009	0.0162
			cultivation and instruction $U_{36}$	0.0802	0.0129
			speech expression $U_{37}$	0.3766	0.0604
	personal feature $U_4$	0.0953	love for students $U_{41}$	0.2371	0.0226
			respect to people $U_{42}$	0.1287	0.0123

Table 3, cont.

		enlightenment U <sub>43</sub>	0.1287	0.0123
		responsibility U <sub>44</sub>	0.2371	0.0226
		confidence U <sub>45</sub>	0.0699	0.0067
		persistence U <sub>46</sub>	0.0699	0.0067
		enterprise U <sub>47</sub>	0.1287	0.0123

In order to facilitate research, only 34 questionnaires of self-evaluation of engineering teachers are selected as samples in W University. Results are calculated according to the weight determined in Table 3 and the results of performance evaluation of AHP are shown in Table 4.

Table 4 Results of performance evaluation of AHP in W university (self competency evaluation of 34 engineering teachers)

No. of teachers	sex	age	title	score of evaluation	percentile score
ZP001	Male	38	lecturer	8.171236	90.79151
ZP002	Male	53	associate professor	8.057526	89.52807
ZP003	Male	46	associate professor	8.051344	89.45938
ZP004	Male	36	lecturer	8.384824	93.16471
ZP005	Male	39	associate Professor	7.957929	88.42143
ZP006	Male	36	lecturer	8.261267	91.79186
ZP007	Male	35	lecturer	8.625388	95.83764
ZP008	Male	36	associate professor	7.031283	78.12537
ZP009	Male	38	associate professor	7.072217	78.58019
ZP010	Male	45	professor	8.247954	91.64393
ZP011	Male	32	lecturer	7.214198	80.15776
ZP012	Male	43	professor	7.595864	84.39849
ZP013	Male	48	professor	8.536483	94.84981
ZP014	Male	44	associate professor	7.567526	84.08362
ZP015	Male	31	lecturer	8.492185	94.35761
ZP016	Male	53	associate professor	8.385913	93.17681
ZP017	Male	55	professor	7.743958	86.04398
ZP018	Male	38	associate professor	8.560462	95.11624
ZP019	Male	44	professor	7.810079	86.77866
ZP020	Male	48	associate professor	8.185521	90.95023
ZP021	Male	36	lecturer	8.419903	93.55448
ZP022	Female	35	lecturer	8.610484	95.67204
ZP023	Female	48	professor	7.95943	88.43811
ZP024	Female	33	assistant	8.210952	91.2328
ZP025	Female	32	lecturer	7.241441	80.46046
ZP026	Female	44	associate professor	8.124543	90.2727
ZP027	Female	36	assistant	8.378991	93.0999
ZP028	Female	32	assistant	8.476565	94.18406
ZP029	Female	58	professor	7.827661	86.97401
ZP030	Female	33	lecturer	7.982569	88.69521
ZP031	Female	34	assistant	7.996101	88.84557
ZP032	Female	40	associate Professor	8.16841	90.76011
ZP033	Female	37	lecturer	7.610157	84.5573
ZP034	Female	34	assistant	8.007975	88.9775

According to the general percentile method, classification is determined as follows: 60 points or less than 60 points are rated as “unqualified”; 60 to 70 points are rated as “qualified”, 70 to 80 points are rated as “medium”; 80 to 90 points are rated as “good” and 90 points or more than 90 points are rated as “excellent”, the assessment results of these 34 engineering teachers are shown in Fig. 1.

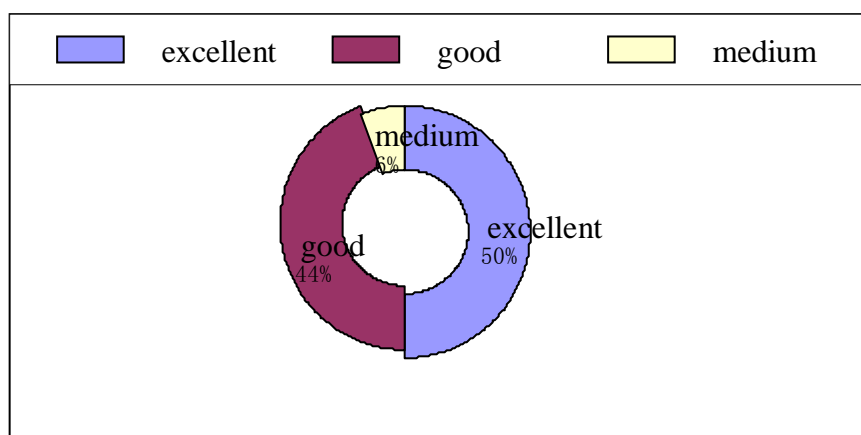


Figure 1. Percentile of evaluation results

### Case of Cluster Analysis of Competency Level of Engineering Teachers in W university

Application of statistics SPSS19.0 software on self-assessment questionnaires of engineering teachers according to the cluster analysis of K-means method, the number of clusters is set to 3 levels of “excellent”, “good” and “medium”, the following clustering results can be obtained in Table 5.

Table 5 Evaluation grade of clustering of self-assessment questionnaire of engineering teachers

No.of teachers	evaluation score by AHP	evaluation grade by AHP	Clustering of K- means	mark of similarities and differences(same=0; different= 1)
ZP001	90.79151	excellent	I (excellent)	0
ZP002	89.52807	good	II (good)	0
ZP003	89.45938	good	I (excellent)	1
ZP004	93.16471	excellent	I (excellent)	0
ZP005	88.42143	good	II (good)	0
ZP006	91.79186	excellent	I (excellent)	0
ZP007	95.83764	excellent	I (excellent)	0
ZP008	78.12537	medium	III (medium)	0
ZP009	78.58019	medium	II (good)	1
ZP010	91.64393	excellent	I (excellent)	0
ZP011	80.15776	good	II (good)	0
ZP012	84.39849	good	I (excellent)	1
ZP013	94.84981	excellent	I (excellent)	0
ZP014	84.08362	good	I (excellent)	1
ZP015	94.35761	excellent	I (excellent)	0
ZP016	93.17681	excellent	I (excellent)	0
ZP017	86.04398	good	I (excellent)	1

Table 5, cont.

ZP018	95.11624	excellent	I (excellent)	0
ZP019	86.77866	good	I (excellent)	1
ZP020	90.95023	excellent	I (excellent)	0
ZP021	93.55448	excellent	I (excellent)	0
ZP022	95.67204	excellent	I (excellent)	0
ZP023	88.43811	good	I (excellent)	1
ZP024	91.2328	excellent	I (excellent)	0
ZP025	80.46046	good	I (excellent)	1
ZP026	90.2727	excellent	I (excellent)	0
ZP027	93.0999	excellent	I (excellent)	0
ZP028	94.18406	excellent	I (excellent)	0
ZP029	86.97401	good	I (excellent)	1
ZP030	88.69521	good	II (good)	0
ZP031	88.84557	good	I (excellent)	1
ZP032	90.76011	excellent	I (excellent)	0
ZP033	84.5573	good	I (excellent)	1
ZP034	88.9775	good	I (excellent)	1

From the results shown in table 5, the results of cluster analysis for competency of engineering teachers is 68% the same compared with the results of AHP method in accordance with the results of samples. What's more, it is worth mentioning that the difference of the rest percentile is that the classification of levels by clustering of K- means is one more level higher than those by AHP method. In other words, some of the competency results by AHP method classified as the level of "good" are classified as the level of "excellent" by clustering of K means in general. Some of the competency results by AHP method classified as the level of "medium" are classified as the level of "good" by clustering of K means in general. In addition, the scores of these competency results calculated by clustering of K means, i.e those scores which are different from those of AHP method are relatively higher compared with scores classified as the level of "medium" or "good" by AHP method. To some degree, the method of clustering of K means is more inclusive and general for embracing topper levels. As for the overall differences of all indicators, clustering analysis does not consider the importance and weight of indicators as some indicators are relatively important or unimportant in the eyes of some people, therefore clustering analysis is somewhat different with AHP method for the reason that weights which may be subjective are considered in the AHP method.

## Conclusion

In the study of competency of engineering teachers in universities, the score of competency evaluation is usually a relative score. In order to obtain the specific results, the results of evaluation often requires division level, such as classification of four levels of "excellent", "good", "qualified" and "unqualified". Methods of traditional classification have strict borders. For instance, if students' achievements are classified according to levels of "excellent", "good", "medium", "qualified" and "unqualified", there is only 1 point difference between 59 points and 60 points, but the classification is quite different as the "unqualified" for 59 points and "qualified" for 60 points. The gap of "good level" between 89 points and 90 points is far less than the gap of "good level" between 80 points and 90 points. Therefore, in terms of evaluation of the competency of engineering teachers, according to five division levels of "excellent", "good", "medium", "qualified" and "unqualified", the above problems can also occur. Cluster analysis can avoid this kind of

problem. As the data mining technology in the era of big data, clustering analysis is used not only to classify the competence level of engineering teachers but also provide basis for decision making for competence- grading of all teachers in other universities. Therefore, it is of theoretical and practical significance for the study in this paper.

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