Research on Teacher Workload Control Strategy Based on Conductive Knowledge Mining

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Abstract

With the extension data mining technology, the conductive knowledge mining method is applied into the management of college teachers' workload. Under the active transformation of control strategy, the conductive effect and its confidence of teachers' workload are calculated, to obtain the conductivity and the conductivity interval, and mine the conductive knowledge of quantitative or qualitative change. A case study of a college shows that the conductive knowledge with a higher support and confidence is helpful for the management departments of colleges to understand the degree of positive or negative effects of some strategies on teachers' research and teaching workload in quantity, so that they can find an appropriate strategy used to control the teachers' workload.

Keywords: Data mining; Extension transformation; Conductive knowledge; Research workload

1. Introduction

The scientific research is an important evaluation indicator of the comprehensive strength of a college or university and a key basis for realizing the combination of "production, study and research" as well as the technology transfer. In order to motivate teachers to invest more energy in research, the college management often develops relevant strategies to enhance the research capability of the college. The data information obtained after implementing the research control strategy, can only support simple information inquiry and statistical work through existing Excel or the research information management system [1-2]. It can only indicate whether the strategy is feasible, but is impossible to further understand the degree of positive and negative effects of the strategy on teachers' research and teaching workload in quantity.

Extension data mining put forward in 2004, after 10 years of research and exploration, has gradually defined its research object and target, and initially formed a set of basic theories and methods of mining extension knowledge. However, there is little applied study on conductive knowledge mining. This paper introduces the conductive knowledge mining method [3] of the extension data mining [4-5] and analyzes the conductive effects of teachers' workload, and discovers the conductive knowledge [6-7] such as conductive object, change of conduction feature value, conductivity and extension classification in terms of teachers' workload under the influence of active transformation [8] of the research control strategy. The purpose of this paper is to provide data reference in "quantity" for research managers to analyze the existing data, so that they can propose appropriate strategies to promote the enhancement of scientific research ability of colleges and universities.

2. Related Conceptions of Extension Data Mining

2.1. Conductive Effects and Conductivity

The information element set [9]

$$\{I_{ij}(t)\} = \{(O_i(t), c_j, v_{ij}(t)), i = 1, 2, \cdots, n; j = 1, 2, \cdots, m\}$$

and a certain information element [10] at t_0 are given respectively as the above and below.

$$I_{i_0j_0}(t_0) = (O_{i_0}(t_0), c_{j_0}, v_{i_0j_0}(t_0))$$

If change φ realize:

 $\varphi I_{i_0j_0}(t_0) = (O_{i_0}(t), c_{j_0}, v_{i_0j_0}(t)) = I_{i_0j_0}(t)$

and when $t > t_0, v_{i_0j_0}(t) = a \neq v_{i_0j_0}(t_0)$, the value of $v_{i_0j_0}(t)$ after conducting transformation φ will not change with t. The conduction transformation $I_{i_0 i_0} T_{I_{i_j}(t_0)}$ of

 φ relative to $\{I_{ij}(t)\}$ makes:

$$I_{i_0 j_0} T_{l_{i_j}(t_0)} I_{i_j}(t_0) = I_{i_j}(t) = (O_i(t), c_j, v_{i_j}(t))$$

when $t > t_0$, the conductive effect [11] of transformation φ relative to the information element $l_{ij}(t)$ will be:

$$\Delta v_{ij} = v_{ij} - v_{ij}(t_0) \tag{1}$$

And the conductivity [3] will be:

$$\gamma_{ij}(t) = \frac{\Delta v_{ij}}{\left|a - v_{i_0 j_0}(t_0)\right|} \tag{2}$$

2.2. Conductive Information Element Set and Conduction Interval

If $\gamma_{ij}(t) = 0$, namely the conductive effect $v_{ij}(t) - v_{ij}(t_0) = 0$, $i \in \{1, 2, \dots, n\}; j \in \{1, 2, \dots, m\}$; $t > t_0$, then I_{ij} is the non-conductive information element of φ , and they are wholly expressed as $I_{\overline{\varphi}}(I_{ij})$. Suppose

$$I_{\varphi}I_{ij} = \{I_{ij}(t)\} - I_{\overline{\varphi}}(I_{ij}) - \{I_{i_0j_0}(t_0)\}$$
(3)

is the conductive information element set [Error! Bookmark not defined.][6] of φ relative to $\{I_{ij}(t)\}$.

And take

$$\gamma_{jmin} = \min_{\substack{1 \le i \le n \\ 1 \le p \le q}} \gamma_{ij}(t_p), \quad \gamma_{jmax} = \max_{\substack{1 \le i \le n \\ 1 \le p \le q}} \gamma_{ij}(t_p) \tag{4}$$

Then the conductivity interval [6] of φ relative to $\{I_{ij}(t)\}$ is $[\gamma_{jmin}, \gamma_{jmax}]$.

2.3. Number of Samples and Confidence

If the information element $l_{ij}(t)$ meets the condition of $L : v_{i7} \in V_j$, then:

$$\left(\varphi I_{i_0 j_0}(t_0) = I_{i_0 j_0}(t)\right) \land \left(I_{ij} \ni L\right) \Longrightarrow (\ell) \{\gamma_{ij} \in [\gamma_{jmin}, \gamma_{jmax}]\}$$
(5)

Where,

$$\ell = (samples, confidence) = \left(nq, \frac{|\{I_{ij}(t_p)\}|}{nq}\right)$$
(6)

 $|\{I_{ij}(t_p)\}|$ is the number of information elements meeting the condition

$$|v_{ij}(t) - v_{ij}(t_0)| > \delta, \ p = 1, 2, \cdots, q$$
 (7)

In the information element set $\{l_{ij}(t)\}$, nq is the number of information elements in the data sheet, and δ is the threshold value [12] relative to the feature c_{j} .

2.4. Simple Correlation Function

Set the value range of x is the finite interval $\langle a, b \rangle$, the positive region is $X = \langle a_1, b \rangle$, $a_1 \ge a$ and the optimal point is b. Then establish a simple correlation function [13]:

$$k(x) = \frac{x - a_1}{b - a} \tag{8}$$

Suppose

$$\alpha_i = k(u_i') - k(u_i) \tag{9}$$

is the correlation difference [6] of information element I_i relative to the evaluation feature d under the transformation φ ;

Suppose

$$\boldsymbol{\beta}_i = \boldsymbol{k}(\boldsymbol{u}_i') \cdot \boldsymbol{k}(\boldsymbol{u}_i) \tag{10}$$

is the correlation product [6] of information element l_i relative to the evaluation feature d under the transformation φ ;

3. The Basic Methods of Conductive Knowledge Mining

There are usually three ways to get knowledge related to the conduction transformation from the database:

(1) Get mining conductive knowledge from multiple characteristics value of one object;

(2) Get mining conductive knowledge from the same characteristics value of multiple objects;

(3) Get mining conductive knowledge from multiple characteristics value of multiple objects.

The general steps of conductive knowledge mining are as follows:

(1) Make data preprocessing in the raw database; the primitive is introduced as expression of relevant information; and form "basic information element base before and after transformation" according to the active extension transformation;

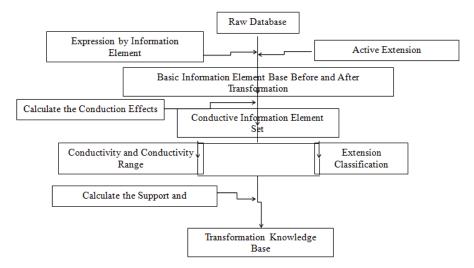


Figure 1. The Basic Methods of Conductive Knowledge Mining

(2) Calculate the conduction effects of the information element in the " basic information element base before and after transformation"; eliminate the object characteristic that the conduction effect should be small or zero; and conductive information element set;

(3) Make conductivity calculation for conductive information element to obtain the transformation about information element's conductivity and conductivity range, and then backtrack and extract the conduction characteristics set and the value range knowledge of conduction characteristics;

(4) Establish correlation function and calculate the relational degree of evaluating characteristic of conductive information element before and after the transmission; combined with correlation difference and correlation product and associated product, mine the extension classification knowledge of conduction information element.

4. Conductive Knowledge Mining of Research Control Strategy

To improve teachers' research level, a college developed the research control strategy in 2013 as below: convert the research achievements into "scores" according to their quantity and quality. The score of each research achievement should be accumulated, and count the research workload of teachers once a year. Based on such statistic results, the ones who have reached the workload standard, will be rewarded for the part exceeding such standard as per the rule of 10 RMB for each exceeding score; and the ones who have not reached the workload standard, will be subject to the deduction of incentive allowances as per the rule of 10 RMB for each unreached score accordingly. The teachers' workload mainly includes teaching workload and research workload. What conductive effect will be produced for these two types of workloads under the action of research control strategies? Next, let's analyze it with the extension conductive knowledge mining method.

4.1. Data Acquisition and Pre-processing

In this case, the data of research workload and teaching workload of teachers in Department of Computer Engineering provided by the Research Office and the Office of Academic Affairs of this university is used as the object of study. The data has been pre-processed, and as the result, the records of teachers whose data is default or does not exist from 2012 to 2015, have been removed. Thus, a table containing teachers' basic information elements before and after the introduction of research control strategy is obtained, as shown in Table 1.

Feature Teacher Name	Teacher Number <i>C</i> 1	Gender C2	Education Background C ₃		Research Workload (scores) <i>C</i> 7	Teaching Workload (class hour) C ₈
$O_{1}(t_{0})$	2009036	male	postgraduate		1560	568
$O_2(t_0)$	2009037	female	undergraduate		100	786
÷	÷	:	÷	÷	:	:
$O_{34}(t_0)$	2012066	female	undergraduate		128	702
$\theta_i(t_i)$	2009036	male	postgraduate		6641	678
$O_2(t_1)$	2009037	female	undergraduate		1039	724
÷	÷	:	÷	÷	:	:
$O_{34}(t_1)$	2012066	female	undergraduate		660	889
$0_1(t_2)$	2009036	male	postgraduate		8195	545
$O_2(t_2)$	2009037	female	undergraduate		600	748
÷	÷	:	÷	÷	:	÷
$O_{34}(t_2)$	2012066	female	undergraduate		924	728
$\theta_1(t_3)$	2009036	male	postgraduate		6879	437
$O_2(t_3)$	2009037	female	undergraduate		3326	633
÷	÷	÷	÷	÷		÷
$O_{34}(t_3)$	2012066	female	undergraduate		2823	659

Table 1. Teachers' Basic Information Elements Table from 2012 to 2015

4.2. Expression of Data Information Element

In this case, suppose $t_0 = 2012$, $t_1 = 2013$, $t_2 = 2014$ and $t_3 = 2015$. Due to the introduction of the research control strategy, the active transformation φ occurs in the information element $I_0(t_0)$, so $\varphi I_0(t_0) = I_0(t_p)$, then:

 $I_0(t_0) = (O_0(t_0), c, v(t_0)) =$ (research work $O(t_0)$, score, 0 RMB/score),

 $I_0(t_p) = (O_0(t_p), c, v(t_p)) = (\text{research work } O(t_p), \text{ score, 10 RMB/score}),$

 $p \in \{1,2,3\}$, and the value of $v(t_p)$ in the three years after the active transformation is not changed.

Under the influence of the above active transformation φ , the change in the information element $l_{ij}(t)$ belongs to conduction transformation, expressed as

$$I_0 T_{I_{ij}} I_{ij}(t_0) = I_{ij}(t_p), i \in \{1, 2, \dots, 34\}, j \in \{1, 2, \dots, 8\}, p \in \{1, 2, 3\}$$

4.3. Calculation of Conductive Effect to Acquire the Conductive Information Element Set

In order to mine the conductive knowledge of research control strategy of teachers' workload, calculate the conductive effect of information element $I_{ij}(t)$, to determine the conductive information element set and the non-conductive information element set according to the effect. Based on Formula (1):

 $\Delta v_{ij} = v_{ij}(t_p) - v_{ij}(t_0), \ i \in \{1, 2, \dots, 34\}, \ j \in \{1, 2, \dots, 8\}, \ p \in \{1, 2, 3\}$

calculate the difference between information element values in Table 1 before and after the transformation is conducted. The result is shown in Table 2.

Feature Teacher Name	Teacher Number C 1	Gender ¢2	Education Background C ₃		Research Workload (scores) C7	Teaching Workload (class hour) C 8
$O_1(t_1)$	0	0	0		5081	110
$O_2(t_1)$	0	0	0		939	-62
÷	:	:	÷	÷	:	:
$O_{34}(t_1)$	0	0	0		532	187
$O_1(t_2)$	0	0	0		6635	-23
$O_2(t_2)$	0	0	0		500	-38
÷	:	÷	:	÷	:	:
$O_{34}(t_2)$	0	0	0		796	25
$O_1(t_3)$	0	0	0		5319	-131
$O_2(t_3)$	0	0	0		3226	-153
÷	:	:	:	÷	:	:
$O_{34}(t_3)$	0	0	0		2695	-43

Table 2. Difference between Information Element Values before and after the
Transformation

According to the data analysis in Table 2, the research workload score was enhanced from 0 RMB /score to 10 RMB/score, while the teaching number, gender, education background and other features are not affected. However, the teachers' research workload and teaching workload were affected a lot by the conduction. According to Formula (3), the non-conductive information element set and the conductive information element set can be obtained as:

$$I_{\overline{\varphi}}I_{ij} = \{ (O_i, c_j, v_{ij}); i = 1, 2, \dots, 34; j = 1, 2, \dots, 6 \}$$
$$I_{\varphi}I_{ij} = \{ (O_i, c_7, v_{i7}), (O_i, c_8, v_{i8}); i = 1, 2, \dots, 34 \}$$

4.4. Extract the Knowledge of Transformation about the Conductivity of Information Elements

After the conductive information element set is obtained, the conductivity of transformation φ for the information element l_{ij} may be calculated through Formula (2), to understand the degree of the influence of research control strategy on teachers' workload. As the research workload score was enhanced from 0 RMB/score to 10 RMB/score after the active transformation was conducted, and kept unchanged for 3 years, then a = 10, $v_{i_0j_0}(t_0) = 0$. Substitute it into Formula (2), and we obtain:

$$\gamma_{ij}(t_p) = \frac{v_{ij}(t_p) - v_{ij}(t_0)}{|a - v_{i_0j_0}(t_0)|} = \frac{v_{ij}(t_p) - v_{ij}(t_0)}{|10 - 0|}, \ i \in \{1, 2, \cdots, 34\}, j \in \{7, 8\}, \ p \in \{1, 2, 3\}$$

Calculate the conductivity and conduction interval of the research workload c_7 and the teaching workload c_8 of conduction feature according to Table 2, as shown in Table 3.

Feature Teacher Name	Research Workload (scores)	Teaching Workload (class hour)
	C 7	с ₈
$O_1(t_1)$	508	11
$O_2(t_1)$	940	-6
:	:	÷
$O_{34}(t_1)$	53	19
$O_1(t_2)$	664	-2
$O_2(t_2)$	50	-4
:	:	:
$O_{34}(t_2)$	80	3
$O_1(t_3)$	532	-13
$O_2(t_3)$	323	-15
:	:	÷
$O_{34}(t_3)$	2670	-4
$\min_{\substack{1 \leq i \leq n \\ 1 \leq p \leq q}} \gamma_{ij}(t_p)$	-286	-58
$\max_{\substack{1 \le i \le n \\ 1 \le p \le q}} \gamma_{ij}(t_p)$	664	34
conduction interval	[-286,664]	[-58,34]

Table 3. Conductivity of Conductive Information Element afterTransformation

According to Tables 1 and 3, substitute them into Formulas (5), (6) and (7), and the following two items of knowledge can be obtained:

- (1) If the information element $I_{i7} = (O_i, c_7, v_{i7})$ meets the condition $L : v_{i7} \in [0.8728]$, then:
- $[\varphi(Research workload O(t_0), score, 0 score/month)]$
 - $= (Research workload O(t_0), score, 10 \ scrores \ /month)] \\ \land (I_{i7} \ni \ L) \Longrightarrow (\ell_7)(\gamma_{i7} \in [-286, 664])$

Where, $\ell_7 = \left(nq, \frac{|\{I_{17}\}|}{nq}\right) = \left(102, \frac{97}{102}\right)$, and the threshold value $\delta_7 = 50$.

This knowledge indicates that when the research workload score is increased to 10 scores/month, if teachers' research workload belonging to [0,8728], the conduction interval will be [-286,664], the number of samples is 102 and the confidence is 97/102, where 97 is the number of information element $|v_{i7}(t_p) - v_{i7}(t_0)| \ge 50$ in Table 2. That means, the confident level that the teachers' research workload has conduction transformation is 95.10%.

(2). If the information element $l_{i8} = (0_i, c_8, v_{i8})$ meets the condition $L : v_{i8} \in [60,1015]$, then:

 $[\varphi(Research workload O(t_0), score, 0 score/month)]$

= (Research workload $O(t_0)$, score, 10 scrores /month)] $\land (I_{i8} \ni L) \Longrightarrow (\ell_8)(\gamma_{i8} \in [-58,34])$ Where, $\ell_8 = \left(nq, \frac{|\{I_{18}\}|}{nq}\right) = \left(102, \frac{98}{102}\right)$, and the threshold value $\delta_7 = 10$.

This knowledge indicates that when the research workload score is increased to 10 scores/month, if teachers' teaching workload belonging to [60,1015], the conduction interval will be [-58,34], the number of samples is 102 and the confidence is 98/102, where 98 is the number of information element $|v_{i8}(t_p) - v_{i8}(t_0)| \ge 10$ in Table 2. That means, the confident level that the teachers' teaching workload has conduction transformation is 95.10%.

4.5. Extension Knowledge Classification of Mining Conductive Information Elements

To further determine which type the change of the conductive information element belongs to, we can calculate the degree of correlations before and after the conduction transformation, to obtain the extension knowledge classification under quantitative change or quality change [14-15].

4.5.1. Calculate the Degree of Correlation of Conductive Information Elements

According to Table 1, calculate the degree of correlation by respectively taking the research workload c_7 and the teaching workload c_8 as the evaluation features of conductive information elements and selecting the simple correlation function with the optimal point on the right.

The value range of teachers' research workload v_{i7} before and after the transformation is [0, 8728], and the basic research workload is 120. Substitute it into Formula (8), and we obtain:

$$k(v_{i7}) = \frac{v_{i7} - a_1}{b - a} = \frac{v_{i7} - 120}{8728 - 0}$$

The value range of teachers' teaching workload v_{i8} before and after the transformation is [60, 1015], and the basic research workload is 320. Substitute it into Formula (8), and we obtain:

$$k(v_{i8}) = \frac{v_{i8} - a_1}{b - a} = \frac{v_{i8} - 320}{1015 - 60}$$

Thus, the degree of the correlation of information element may be obtained, as shown in Table 4.

Feature Teacher	Research Workload (scores)	Teaching Workload (class hour)
Name	c7	<i>c</i> ₈
$O_{1}(t_{0})$	0.1650	0.2599
$O_2(t_0)$	-0.0023	0.4879
:	÷	:
$O_{34}(t_0)$	0.0009	0.4002
$O_{1}(t_{1})$	0.7471	0.3748
$O_2(t_1)$	0.1052	0.4232
:	:	:
$O_{34}(t_1)$	0.0619	0.5955
$O_1(t_2)$	0.9252	0.2356
$O_2(t_2)$	0.0550	0.4479
÷	:	:
$O_{34}(t_2)$	0.0921	0.4268
$O_1(t_3)$	0.7744	0.1229
$O_2(t_3)$	0.3673	0.3280
:	:	:
$O_{34}(t_3)$	0.3097	0.3550

Table 4. Correlation Degree of Conductive Information Element before and
after the Transformation

4.5.2. Analysis of the Extension Classification of Conductive Information Elements

According to the degree of correlation of the two evaluation features in Table 4, calculate the correlation difference and the correlation product according to Formula (9) and Formula (10) to analyze the extension classification of each conductive information element.

The correlation difference is:

$$\alpha(v_{ij}) = k(v_{ij}(t_p)) - k(v_{ij}(t_0))$$

And the correlation product is:

 $\beta(v_{ij}) = k(v_{ij}(t_p)) * k(v_{ij}(t_0))$

Where, $i \in \{1, 2, \dots, 34\}, j \in \{7, 8\}, p \in \{1, 2, 3\}$. The extension classification of the conductive information elements were classify according to the classification standard^[Error! Bookmark not defined.] of evaluating information elements, as shown in Table 5 and Table 6.

	$k(v_{i7})$	$\alpha(v_{i7})$	$\beta(v_{i7})$	Extension Classification
$O_{1}(t_{0})$	>0			
$O_2(t_0)$	<0			
÷	:			
$O_{34}(t_0)$	>0			
$\theta_1(t_1)$	>0	>0	>0	Effect-increasing transformation of positive qualitative change
$O_2(t_1)$	>0	>0	<0	Positive qualitative change
÷	:	÷		:
$O_{34}(t_1)$	>0	>0	>0	Effect-increasing transformation of positive qualitative change
$O_1(t_2)$	>0	>0	>0	Effect-increasing transformation of positive qualitative change
$O_2(t_2)$	>0	>0	<0	Positive qualitative change
÷	:			1
$O_{34}(t_2)$	>0	>0	>0	Effect-increasing transformation of positive qualitative change
$O_1(t_3)$	>0	>0	>0	Effect-increasing transformation of positive qualitative change
$O_2(t_3)$	>0	>0	<0	Positive qualitative change
:	1	1	1	1
$O_{34}(t_3)$	>0	>0	>0	Effect-increasing transformation of positive qualitative change

Table 5. Extension Classification of Conductive Information Elements in
Terms of Research Workload c_7

Table 6. Extension Classification of Conductive Information Elements in
Terms of Teaching Workload c_{g}

	$k(v_{i8})$	$\alpha(v_{i8})$	$\beta(v_{i8})$	Extension Classification
$O_{1}(t_{0})$	>0			
$O_2(t_0)$	>0			
:	:			
$O_{34}(t_0)$	>0			
$\theta_i(t_i)$	>0	>0	>0	Effect-increasing transformation o positive qualitative change
$O_2(t_1)$	>0	<0	>0	Effect-decreasing transformation of positive qualitative change
:	:	1	:	:
$O_{34}(t_1)$	>0	>0	>0	Effect-increasing transformation o positive qualitative change
$\theta_1(t_2)$	>0	<0	>0	Effect-decreasing transformation of positive qualitative change
$O_2(t_2)$	>0	<0	>0	Effect-decreasing transformation of positive qualitative change
:		1	:	÷
$O_{34}(t_2)$	>0	>0	>0	Effect-increasing transformation o positive qualitative change
$\theta_1(t_3)$	>0	<0	>0	Effect-decreasing transformation of positive qualitative change
$O_2(t_3)$	>0	<0	>0	Effect-decreasing transformation of positive qualitative change
:	:	1	:	÷
$O_{34}(t_3)$	>0	<0	>0	Effect-decreasing transformation of positive qualitative change

4.5.3. Acquisition of Extension Classification Knowledge of Conductive Information Elements

According to Table 5, there is extension classification knowledge as shown in Figure 1 in terms of the evaluation of feature research workload. Where, the number of conductive information elements is $|\{I\}|=102$, the number of elements in positive region before the transformation was conducted is $|E_+|=75$, and the number of elements of correlation difference $\alpha_i > 0$ in positive region after the transformation was conducted is $|E_+(\varphi)|=51$. Substitute them into the formula for calculation of the support and confidence of the positive quantification effect-increasing transformation, and we obtain:

$$\ell_{c_7} = (\text{support, confidence}) = \left(\frac{|E_+|}{|\{I\}|}, \frac{|E_+(\varphi)|}{|E_+|}\right) = \left(\frac{75}{102}, \frac{51}{75}\right) = (73.53\%, 68.00\%)$$

This conductive knowledge indicates that the basic workload of 120 scores can be completed before the transformation of the teachers' research workload. After the scoring standard for research work was increased to 10 scores/month, the completion condition of the workload was further improved. At the same time, the support and confidence were respectively 73.53% and 68.00%, and it was the most important and accurate knowledge among the seven items of extension classification knowledge about the evaluation feature research workload.

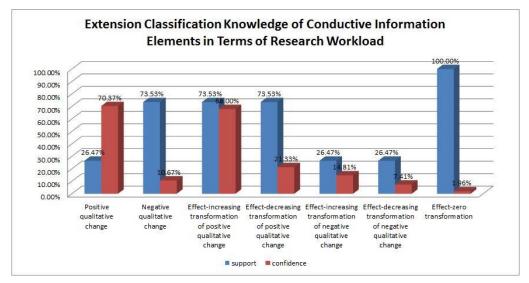


Figure 2. Extension Classification Knowledge of Conductive Information Elements in Terms of Research Workload

According to Table 6, there is extension classification knowledge as shown in Figure 2 in terms of the evaluation of feature teaching workload. Where, the number of conductive information elements is $|\{I\}|=102$, the number of elements in positive region before the transformation was conducted is $|E_+|=87$, and the number of elements of correlation difference $\alpha_i < 0$ in positive region after the transformation was conducted is $|E_+(\varphi)|=68$. Substitute them into the formula for calculation of the support and confidence of the positive quantification effect-decreasing transformation, and we obtain:

$$\ell_{c_{\rm g}} = (\text{support, confidence}) = \left(\frac{|E_+|}{|\{I\}|}, \frac{|E_+(\varphi)|}{|E_+|}\right) = \left(\frac{87}{102}, \frac{68}{87}\right) = (85.29\%, 78.16\%)$$

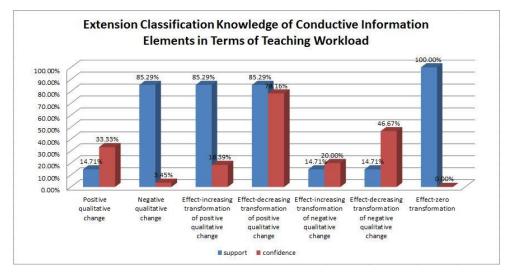


Figure 3. Extension Classification Knowledge of Conductive Information Elements in Terms of Teaching Workload

This conductive knowledge indicates that the basic workload of 320 scores can be completed before the transformation of the teachers' teaching workload. After the scoring standard for research work was increased to 10 scores/month, the completion condition of the teaching workload was reduced. At the same time, the support and confidence were respectively 85.29% and 78.16%, and it was the most important and accurate knowledge among the seven items of extension classification knowledge about the evaluation feature research workload.

By integrating the above-mentioned conductivity knowledge and the extension classification knowledge obtained through the extension data mining technology, it can be concluded that the teachers' research workload was significantly improved after the score for the research was increased to 10 scores/month, but the teaching workload decreased to a certain extent, and the focus of teachers' work inclined to the scientific research.

5. Conclusion

In this paper, the conductive knowledge mining method is applied to the management of college teachers' workload. The conductive knowledge with high support and confidence is obtained, which can help the management departments of colleges and universities to learn that the effects of a strategy on teachers' workload are positive or negative, as well as the degree of effects, so that they can determine the most appropriate strategy to promote the enhancement of teachers' research. Through real case study results, it illustrates that the knowledge mined is helpful to adjust relevant control strategy. Next, we will conduct in-depth research on issues like the realization of the extension clustering knowledge mining ^[6], extension knowledge mining on the basis of knowledge-base, as well as conductive knowledge mining system on computer, so as to make preparation for developing the strategy generation system^{[16][17]} based on the extension data mining.

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References

- [1] Jia Lijie, Yan Shuting and Zhu Qingxiang. Scientific Research Management System Based on the Quality Management System [J]. Chinese University Science & Technology, 2011 (8): 24-25.
- [2] Wang Xinyu. Research Management System Based on .Net Framework [J]. Computer Systems & Applications, 2014, 23 (5): 48-53.
- [3] Li Xiaomei. Extension Data Mining Based on Products Sales According to Change of CPI [J]. Mathematics in Practice and Theory, 2009, 39 (4): 178-183.
- [4] Yang Chunyan and Cai Wen. Research Progress in Extension Data Mining [J]. Mathematics in Practice and Theory, 2009, (39) 4: 134-141.
- [5] Wang Jianlin, Yang Yinsheng and Wang Xueling. Evaluation of Land Use in Yellow River Delta Based on Extension Data Mining [J]. Journal of Jilin University Engineering and Technology Edition, 2012 (1): 479-483.
- [6] Li Zhong, Chen Xinfang, Yu Guoqing, Prediction Model of Yellow River Break-up Date Based on Extension Data Mining. [J]. Water Resources and Power, 2013, 31 (9): 1-3, 19.
- [7] Fang Yaomei and He Wanpeng. Application of Extension Data Mining in Teaching Quality Evaluation of Higher Institution [J]. Mathematics in Practice and Theory, 2009 (4): 82-87.
- [8] Li Xiaomei, Yang Chunyan and Li Weihua. Conductive Knowledge Mining Based on Stock Market Affected by Refined Oil Tax Reform [J]. Application Research of Computers, 2010, (27) 8: 2865-2868.
- [9] Ye Guangzi and Li Weihua. Application of Extension Data Mining in Teachers' Scientific Research Evaluation [J]. Mathematics in Practice and Theory, 2015, 45 (12): 53-59.
- [10] Zhu Lingli, Li Weihua and Li Xiaomei. Research on Extension Knowledge Mining Software for Customer Value [J]. Journal of Guangdong University of Technology, 2012, (29) 4: 7-13.
- [11] Yang Chunyan and Cai Wen. Research on Acquisition of Extension Classification Knowledge Based on Extension Set [J]. Mathematics in Practice and Theory, 2008, (38) 16: 184-191.
- [12] Ye Guangzi, Li Weihua and Li Shufei. Component-based Design and Realization of Extension Strategy Generation System [J]. CAAI Transactions on Intelligent Systems, 2010, 4 (4): 366-371.
- [13] Li Weihua and Yang Chunyan. Development of Extension Strategy Generation Software Based on HowNet [J]. Science & Technology Review, 2014, (32) 36: 32-36.
- [14] Yang Chunyan, Li Xiaomei, Chen Wenwei Extension Data Mining Method and Its Computer Implement [M]. Beijing: Science Press, 2010.
- [15] Yang Chunyan and Cai Wen. Extenics [M], Beijing: Science Press, 2014.
- [16] Zhao Yanwei and Su Nan. Extension Design [M], Beijing: Science Press, 2010.
- [17] Cai Wen, Yang Chunyan, Chen Wenwei, Extension Set and Extension Data Mining [M]. Beijing: Science Press, 2008.

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