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The Model of Information Process of the Best Variant Choice

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Abstract: The developed model of information process of the best variant choice has been observed in present research. The development of formal estimation methods of staff competence has been investigated. The mathematical model, allowing relating quantitative staff characteristics to each other, measured even by different scales with intuition idea of them will be presented. The decision of problem to estimate staff competence is reduced to general task of choice and decision.

Key words: Expert estimations, staff competence, task choice, decision, formal methods of estimations

INTRODUCTION

The effective manage of educational process is one of the important management tasks in university system which consists of large number of persons acting in this process. The creation of optimal conditions for increasing of professional education quality becomes one of direction of a modern conception of Russian education. The modern conception determines the university development as dynamic, self-developing and adapting open educational system, based on compliance with state standards. The system has reference point to using of high-technological educational methodic and uses principles and mechanisms of manage, based on criteria of quality.

To increase effectiveness of educational service the university has to use all existing opportunities (Terent'eva and Kulakova, 2012). In present cases, the creation of competitive advantages becomes one of the main goals of members of the education market. Effective work activity of faculty members (staff) of university is key factor for increase of competitive advantages of the university (Litvinova and Cherkasov, 2012).

During manage of educational process in the university the departments has a task to distribute instructions in view of staff competence toward subject. So, staff influences on subject. The aim of this research is to develop estimation model of staff competence to determine subject.

MAIN PART

Sub-system of pre-preparation of initial data: The present sub-system creates matrix of distance between candidates. The enter data are multiplicity of candidates, effected on subject and properties. At mathematical treatment of experimental data with goal of establishment of empirical regularities as initial data will be results of observation (passive experiment) or results of some active experiments. For effective using of computer at treatment of these data the results will be presented as rectangular Table "Object-Properties" (TOP) with dimension of M×N which is divided on K sub-table. Line of TOP corresponds to observed candidates, influencing on subject and column corresponds to values, reflected candidate properties. Every table combines candidates of one class.

Suggest, initial data, obtained in result of observation and (or) experiments are set in natural mapping. It means that components of candidate description in general case have different physical meaning and they are measured in different scales and cannot be matched with each other. Therefore, it is necessary to expose natural TOP by standardization what leads to standard form when mathematical expectation and scatter of each property in standard TOP are equal to 0 or 1.

For estimation with using computer of similarities and differences of candidates, presented in TOP, it is necessary to add a formal measure of similarities (or differences) to compare candidates with each other.

The candidate description is considered as vectors in N-dimensional features space of E^N. The hypothesis of compactness affirms that a task of detection in them empiric regularities must consist of 2 principal important features:

- TOP must have the solution
- Compactness means that points in space of E^N of one class is located closer to each other, than to points in space of E^N of other class

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The hypothesis of compactness in this geometrical setting allows adding the difference measure in research field as distance between points (vectors) in feature space of E^N (Blejhut, 1986). In this case, it is possibly to Eq. 1 the concept of distance D (x_1, x_2) between candidates of $\bar{x}_1$ and $\bar{x}_2$, set by description and (Eq. 2) the concept of distance from candidate to candidate class Q:

$$D(x,Q) = \inf\{D(\bar{x},\bar{y})\forall y \in Q\} \quad (1)$$

$$D(Q_1,Q_2) = \inf\{D(\bar{x}_1,\bar{x}_2)\forall x_1 \in Q_1, x_2 \in Q_2\} \quad (2)$$

Because of candidate features aren't in qualitative scales, it is necessary to use Hamming distance (Eq. 3) for comparison of candidates (Yang and Wang, 2007; Jegou *et al*., 2008; D'hulst and Rodgers, 1999; Norton and Salagean, 2000):

$$D_h(x_1,x_2)\frac{1}{N}\sum_{j=1}^{N}|x_{1j},x_{2j}| \quad (3)$$

In which, the candidate difference is expressed by number of feature discrepancies of compared research objects. In case qualitative scale all features are binary, their values have only two types: "Yes" or "No" (1 or 0), Hamming distance D_h is = 1 for candidates with different descriptions. For research objects with coinciding features from description list $D_h = 0$.

In present research, TOP is interpreted as feature distribution in M-dimensional space of objects. For this it is used distance matrix M×M where M: candidate number in initial TOP. Its elements are distance from one candidates to other one, calculated according to initial TOP using Hamming formulas $D_h(x_i, x_j)$ I, j = {1, 2, ..., M}.

SUB-SYSTEM OF CANDIDATE AGGREGATION

The task of element aggregation takes one of the main places in applied analysis of empiric data. Since, elements are the candidates in present research, then matrix of proximities and class list are used as initial date and solution, respectively. Class list is list of candidate groups close to each other in feature space (Kompanec *et al*., 1992). Since, variation method unlike heuristic one allows finding, then this method is applied in our task of candidate aggregation (Zhilyakov *et al*., 2014; He and Wu, 2007; He, 2007; Bruce, 2014; Abdou and Soliman, 2005).

The candidate aggregation is carried out using optimization algorithm "λ-krab" (Preparata and Shejmos, 1989). This algorithm is applied for element aggregation set by matrix of distance between them and is result of formalization of some human representation about quality of partition of elements of initial multiplicity. The process of algorithm consists of two stages. The first stage is association of elements with each other. For this the Nearest Unclosed Way (NUW) or minimum spanning tree is constructed. The spanning tree represents loop-free graph in which the as summits and edges are drawn between the closest elements. NUW unites all elements of initial multiplicity wherein sum of edge length, included in NUW is minimal. The first stage of our algorithm is ending at NUW construction.

During the second stage algorithm sequentially cuts the NUW edges, beginning from the maximal and calculating the value of functional quality for each cutting. The process of cutting is stopping and algorithm is ending its work when the value of functional quality after maximal point decreases.

The first preference is formalized with help of estimation of average length of the interior edges of the cub-multiplicity (Eq. 4). It creates the value of common measure of proximity of interior points of classification (Cipileva, 2004):

$$R = \frac{1}{K}\sum_{q=1}^{K}\left(\frac{1}{M_g - 1}\sum_{i=1}^{M_g - 1} r_{ig}\right) \quad (4)$$

Where:

r_{ig} = The length of ith edge in g-dimensional sub-multiplicity
Mg = Element number, aggregated in g-dimensional sub-multiplicity

The second preference is formalized with help of the estimation of average length of edges, connecting sub-multiplicity in NUW together (Eq. 5):

$$D = \frac{1}{K-1}\sum_{g=2}^{K} d_g \quad (5)$$

where, d_g the edge length in NUW between g- and (g-1) sub-multiplicity. Larger distance between sub-multiplicity leads to larger value of D. The third preference is formalized using the estimation of average gradient (the distance difference between elements of sub-multiplicity (Eq. 6)).

$$G = \frac{1}{K-1}\sum_{g=2}^{K} r_{min}/d_g \quad (6)$$

where, r_{min} minimal of joined to d_g edges g- and (g-1) sub-multiplicity. The fourth preference is formalized using the estimation of uniform distribution of elements in sub-multiplicity (Eq. 7):

$$H = K^K \prod_{g=1}^{k} M_g / M \tag{7}$$

which is changed from 0 to 1. The quality of dividing elements onto sub-multiplicities in algorithm is estimated by functional of L = Ln (DH/GR) which formalizes the human representation about quality of dividing and aggregation elements.

SUB-SYSTEM OF DETERMINATION OF CANDIDATE EFFECT ON SUBJECT

In previous sub-systems, the optimization of candidates influenced on subject has been done. Now, it is necessary to determine the degree of influence of each candidate on subject. Suggest, our task is related to uncertainty, since we will be use the method of expert estimation.

The choice of expertize methodic follows from the task. The expert number is determined from the next Eq. 8:

$$K = Z^2(p)V^2 / E^2 \tag{8}$$

Where:

Z(p) = An argument of probability interval
V = Variation coefficient, E relative error of choice

From Eq. 8 follows that the expert number K must be more than coherence of their opinion and more than probability P what guarantees the implementation. It leads to increase of variation coefficient and decrease of mistake number. The treatment of obtained result consists of 3 stages.

The first stage is related to expert ranking, i.e., to determination of degree of confidence to their opinions. The expert ranking occurs according to the degree of the credibility of their judgments. For this it is necessary to calculate weight coefficients on base of their qualification, specialization and degree of understanding of problem. This dependence takes the form of multiplicative or additive weigthing (Eq. 9):

$$K_{Эi} = K_{ki} \times K_{ci} \times K_{3i}, i = \overline{1,n} \tag{9}$$

Where:

$K_{Эi}$ = Weight coefficient of ith expert
K_{ki} = Qualification coefficient
K_{ci} = Specialization coefficient
K_{3i} = Coefficient of degree of understanding of problem
n = Expert number

The first coefficient of them is determined by formal feature and two others by self-conception. On the second stage in view of weight coefficient of expert significance of one or other characteristic is estimated. The third stage identifies a question about the degree of opinion coherence of expert group. If the expert opinions are not coherence, it is necessary to increase the expert number. To ease of expert's work it is suggested to estimate the degree of candidate influence on subject in view of ranking number, where larger degree of influence corresponds to smaller number (Koroleva, 2010). After entering of ranking weight their treatment is started with aim to receive the back values to initial ranking coefficients (Eq. 10):

$$K_{oij} = \frac{1}{K_{3ij}}, i = \overline{1,n}, j = \overline{1,m} \tag{10}$$

Where:

K_{3ij} = Ranking coefficient of understanding of ith expert of the degree of candidate influence on the subject
n = Expert number
m = Candidate number per subject

Further, coefficients are undergone normalization with goal of their transformation into specific weight (Eq. 11):

$$K_{3Hij} = \frac{K_{ij}}{\sum_{j=1}^{m} K_{ij}} \tag{11}$$

The operation of multiplicative weighting violates the normalization condition of coefficients, what requests second normalization. Moreover, unlike previous steps it is necessary to perform normalization by lines (Eq. 12), i.e:

$$K_{3ij}^{Д} = \frac{K_{3ij}}{\sum_{i=1}^{n} K_{3ij}} \tag{12}$$

Where:

$K_{3ij}^{Д}$ = Normalization coefficient of i-th expert by jth candidate
K_{3ij} = Non-normalization coefficient

In result, we received differential coefficients of experts allowing interpreting the degree of their authority. The task of the second stage is to determine weight coefficients of candidates what shows their "importance". The processing scheme of expert data consists of next steps:

- The transformation of ranking estimations into normalization coefficient
- The weighting of normalization coefficient by expert coefficients

- The creation of differential normalization coefficients
- The receiving of integral normalization estimations

The first step is performed according to rules of treatment of coefficient of expert understanding of subject problem (Eq. 13). The second step:

$$K_{oij} = K_{Hij} \times K^{Д}_{Эij}, i \in \{n\}, j = \overline{1, m} \quad (13)$$

Where:

K_{oij} = Weight coefficient of jth object, obtained on base of ith expert

$K^{Д}_{oij}$ = Differential weight coefficient of jth expert by ith sub-system

The third step is related to differentiation of expert opinion on importance of ranking object with view of competence. Normalization of estimation, obtained during the second step is performed by lines (Eq. 14):

$$K_{oj} = \frac{K_{oij}}{\sum_{i=1}^{n} K_{oij}} \quad (14)$$

During this step the coherence of expert opinion is checked using dispersion and variation coefficients. The coherency level is high if $\upsilon \leq 0.33$. During the fourth step the desired integral normalized object estimations are formed Eq. 15:

$$K^{M}_{oj} = \frac{\sum_{i=1}^{n} K^{Д}_{oij}}{\sum_{i=1}^{n}\sum_{j=1}^{n} K^{Д}_{oij}}, i = \overline{1, n} \quad (15)$$

Sub-system decision: This sub-system represents the choice of one of some candidate multiplicities. For this we have found variant with maximal result value, i.e., the goal of choice is max e_i. Thus, the choice of optimal variant is made with help of criteria (Eq. 16):

$$E_0\{E_{i0} \mid E_{i0} \in E \wedge e_{i0} = \max_i e_i\} \quad (16)$$

To receive to one best variant it is necessary to add estimated (target) function (Mushok and Miller, 1990; Svanberg *et al*., 2003). Decision matrix $||e_{ij}||$ reduces to one column. Some result e_{i2} corresponds to each variant E_i. This result e_{i2} characterizes in particularly, all consequences of this decision. The choice procedure is represented by analogy with criteria application (Eq. 14). The best result e_{i2} has follow form (Eq. 17):

$$\max_i e_{i2} = \max_i(\min_j e_{ij} + \max_j e_{ij}) \quad (17)$$

For result formation we will proceed from compromise between optimistic and pessimistic approaches and from requests of choice (Makarov and Vinogradova, 1992; Leyva-Loopez and Fernandez-Gonzalez, 2003). In the task, we were focused on worst case and were attributed the worst of possible result to each of alternative variant. After this, we were chosen the best variant. For each other interior condition the result may be only equal to this one or better. Considering situation of decision, the necessary of application of minimax criterion (MM) occurs (Eq. 18-21):

$$\max_i e_{i2} = \max_i(\min_j e_{ij}) \quad (18)$$

at:

$$Z_{MM} = \max_i e_{i2} \quad (19)$$

and:

$$e_{i2} = \min_j e_{ij} \quad (20)$$

$$E_0 = \{E_{i0} \mid E_{i0} \in E \wedge e_{i0} = \max_i \min_j e_{ij}\} \quad (21)$$

where, Z_{MM} a single function of MM-criterion. The rule of decision choice according to MM-criterion is interpreted as: decision matrix $||e_{ij}||$ is added else one column from least results e_{ij} of each line. Then it was chosen those variants E_{i2} which have max values e_{i2} of this column in line.

SUMMARY

The developed mathematical model of information process of the best variant choice allows manage more effectively by staff. The performance of most important tasks will be provided to most competent candidates. Model considers the expert opinion in view of their competence.

CONCLUSION

The developed model of information process of the best variant choice has been represented in view of mathematical model. Formal method of estimation of staff competence for implementation of instructions, represented as mathematical model has been suggested. It allows relating quantitative staff characteristics to each other, measured even by different scales with intuition idea of them. Because of presented methodic it is possible to lead the candidate optimization. This eases the construction of model of candidate choice for increasing of educational manage.

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