

OPERATING MODEL OF KNOWLEDGE QUANTUM ENGINEERING FOR DECISION-MAKING IN CONDITIONS OF INDETERMINACY

Liudmyla Molodykh, Igor Sirodza

Abstract: The operating model of knowledge quantum engineering for identification and prognostic decision-making in conditions of α -indeterminacy is suggested in the article. The synthesized operating model solves three basic tasks: A_T -task to formalize tk-knowledge; B_T -task to recognize (identify) objects according to observed results; C_T -task to extrapolate (prognosticate) the observed results. Operating derivation of identification and prognostic decisions using authentic different-level algorithmic knowledge quantum (using tRAKZ-method) assumes synthesis of authentic knowledge quantum database (BtkZ) using induction operator as a system of implicative laws, and then using deduction operator according to the observed tk-knowledge and BtkZ a derivation of identification or prognostic decisions in a form of new tk-knowledge.

Keywords: operating model, decision-making object, knowledge quantum database, target feature, method of different-level algorithmic knowledge quantum, implicative law.

ACM Classification Keywords: I.2.3 Deduction and Theorem Proving; I.2.4 Knowledge Representation Formalisms and Methods; I.2.5 Programming Languages and Software

Introduction

Knowledge-oriented modelling of human being's intellectual skills to make decisions in conditions of indeterminacy to recognize patterns and prognostic situations for artificial intelligence systems (AIS) is being developed in the article. Operating model for knowledge quantum engineering for decisions derivation in conditions of indeterminacy, which is based on using the **method of authentic different-level algorithmic knowledge quantum or portions (tRAKZ-method)** is suggested. The existing artificial neural networks (ANN) and knowledge engineering methods, based on frame, production and other knowledge models, are not effective enough because of the imperfection of representation ways and computer knowledge manipulation. Unlike these approaches the suggested model has a form of strictly formalized knowledge quantum, different in the level of complexity (tk-knowledge). Such tk-knowledge as substantial algorithmic structures of authentic data allow computer manipulation of knowledge using an finite predicates algebra and vector-matrix operators, and also inductive synthesis of **knowledge quantum database (BtkZ)** while teaching computer using selective plot examples of situations from the concrete data domain.

1. Target setting

The model-based process of **human's classification** and **prognostic** decision-making in conditions of *indeterminacy* is always aimed (motivated by a target criterion) at the **decision-making object (DMO)**, which can be described with a set of characteristics (features), measured in different scales and allowing logical representation. **Target** features are also contained in this set. Their values determine the **class** and **pattern** of the considered **DMO**. To **identify** the class (pattern) of DMO, i.e. to **make a classification decision**, means to define a value of the **target feature** according to the observed initial characteristics, relying on the **knowledge quantum database (BtkZ)**, represented by **classification law** systems. Analogically to make a **prognostic decision** it is necessary to have a **prognostic BtkZ**, allowing to define the value of the **target prognostic feature** on the segment $t+\Delta t$, according to the situation on the time segment t .

The discussed α -indeterminacy is characterized by such limitations:

- data about DMO are of different type (i.e. measured in quantitative as well as in qualitative scales) and can be reached in incomplete volumes and from different sources (experts, technical documentation, reference books, instruments measurements etc.);

- the target criteria are given implicitly, it is unknown which ones, in what quantity and how to select informative features of DMO according to targets of decision-making;
- the rules of making classification and prognostic decisions are unknown, and also the inductive principles of their building by teaching on selective experimental data are unknown too;
- the sought rules of decision-making are impossible to be defined by regular calculus of approximations directly, but it is possible to create knowledge engineering tools to model and imitate intellectual human's skills to find solutions, relying on intuition and knowledge database.

In α -indeterminacy the **authentic k-knowledge (tk-knowledge)** are used.

The main task of this article is to create a method of synthesis for operating model in knowledge quantum engineering to derive classification and prognostic decisions in conditions of α -indeterminacy. In general this task is deduced to solving three basic tasks [Sirodzha, 2002]:

1. **A_t-task** for formalization of tk-knowledge;
2. **B_t-task** for object recognition (identification) according to observation results;
3. **C_t-task** for extrapolation (prognostic) of observation results.

In the **A_t-task** it is required to define the terms "**tk-knowledge**" and "**tRAKZ-models**" formally in conditions of α -indeterminacy, to describe their algorithmic design using quantum structuring of different-type data about DMO considering its semantics in a concrete data domain.

A_t-task is described formally using the multiple four:

$$A_t = \langle S, K_t, \Pi_t, Q_t \rangle \quad (1)$$

and consists in building the class M_t of substantial algorithmic structures and operating tools for manipulating them on a character language S from a set of letters, numbers, special symbols and algorithmic operations of algorithm theory on the basis of using rules for constructing t-quantum Π_t to terminal t-quantum from K_t with a help of finite set Q_t of semantic codes. Under semantic code $tk_s \in Q_t$ ($s=0,1,2,\dots$) we assume symbols, coding t-quantum, which corresponds the form and content of authentic knowledge of level s .

The **B_t-task** is to synthesize **recognizing tRAKZ-models** and algorithms to manipulate tk-knowledge to define values of **target characteristic** for the recognized DMO, i.e. its **identification** with the given reliability according to the external observations, relying on the preliminary cumulated BtkZ.

The **C_t-task** is to synthesize **prognostic tRAKZ-models** and algorithms for manipulation tk-knowledge to **predict** with the given reliability of **DMO permanent characteristics** values according to the measured values of the observed characteristics, relying on the preliminary built BtkZ.

To solve B_t- and C_t-tasks it is required:

- 1) **to synthesize the induction operator** $INDS(tk_2\Sigma_0; AZ; tk_2\overline{\Sigma_{BM}})$ for inductive derivation of the sought BtkZ from a set of selected teaching tk-knowledge, where in brackets the parameters of INDS operator are shown: $tk_2\Sigma_0$ - teaching selective tk-knowledge of the 2nd level; AZ – operating algorithm of inductive derivation for BtkZ as new knowledge; $tk_2\overline{\Sigma_{BM}}$ - minimized BtkZ in the form of a matrix t-quantum of the 2nd level as a system of implicative laws.
- 2) **to synthesize the deduction operator** $DED(tk_2\Sigma_0; tk_1Y_\omega; AL; tk_sR)$ for deductive derivation of the sought decision as a new tk-knowledge of the level s ($s=1,2$) tk_sR in observations tk_1Y_ω for DMO ω , relying on $BtkZ = tk_2\overline{\Sigma_{BM}}$, where AL is a deduction *algorithm*.

2. Algorithmic Formalization and Vector-Matrix Representation of tk-knowledge (A_t-task)

The general structure of **t-quantum of knowledge (tk-knowledge)** has two compounds: *semantic* and *informational* to represent a *knowledge portion* about DMO conditions in **semantic, informational** and **algorithmic** aspects at the same time. It is supposed that a portion (quantum) of knowledge about the DMO

condition describes some authentic quantum event (QE) in a production form “*message - consequence*” according to the scheme (2)

$$\begin{aligned} & \text{IF (logical combination of messages } e_i), \text{ THEN (consequence } C_j), \\ & i = 1, k; j = 1, h. \end{aligned} \tag{2}$$

Semantic compound of t-quantum in a form of **special structure of data** represents **meaning information** about this **QE**, showing the *scales for measuring* the DMO features, *semantic code* and quantum purpose as *knowledge model* about facts or laws. **Semantic code** from the set Q_t has a symbolic form $tk_s Y_\omega$, k is a quantum symbol; $s \in \{0,1,2,\dots\}$ is a level, Y is a name and $\omega \in \{p, tr, b, t,\dots\}$ – quantum status (**p**recondition, **t**arget, **b**asic, **t**erminal).

Information compound describes different-type features (characteristics) of DMO in a sectioned (domain) vector-matrix form, suitable to *manipulate tk-knowledge* and *logical derivation* using **computer algebra**. In a substantial and formal representation the domains d_j meet *non-target* (precondition) and *target* features of DMO, they are called **active** and are separated by a symbol “ : ”. Binary components of active domains $\alpha_j \in d_j$ correspond to the features values. All the active domains define the QE logics, as far as a postulate is taken about the fact that active domains are connected with a **conjunction** (“:” is a strap “^”), the compounds in domains – with a **disjunction** (“,” is a strap “v”), and precondition domains to a target – with an **implication** (“ \Rightarrow ”) in a form of (2). The logics of QE can be described in *sentential formulas of propositional logic* or in *finite predicates*, where the arguments are components of α_j domains.

The main idea of **strictly formalization** is in axiomatic building of tRAKZ-model on the basis of postulating the three **terminal** quanta $tk_1 y_T$, $tk_0 a_T$, $tk_1 b_T$ and using operators of **superposition** (Π -operator) known in the theory of algorithm, a **string concatenation** (CON(•)-operator) and a **column concatenation** (CON[•]-operator).

The *generalized terminal* quantum $tk_1 y_T$ represents a **vector of domains**, corresponding to different-type features x_1, \dots, x_n DME with values (in the domain components) from the finite sets X^j , ($j=1,2,\dots, n$): $X^1 = \{\alpha_1^1, \dots, \alpha_{r_1}^1\}, \dots, X^n = \{\alpha_1^n, \dots, \alpha_{r_n}^n\}$. The *generalized* quantum $tk_1 y_T$ has a form:

$$tk_1 y_T = [d_1 : d_2 : \dots : d_n] = [\alpha_1^1, \dots, \alpha_{r_1}^1 : \alpha_1^2, \dots, \alpha_{r_2}^2 : \dots : \alpha_1^n, \dots, \alpha_{r_n}^n] , \tag{3}$$

where $tk_1 \in Q_T$; name $y_T \in S_v$.

The *generalized terminal selecting* quantum $tk_0 a_T$ is described with a **selection function** $V_k^{(l)}$ of the argument α_k from t-consequence of numbers or symbols:

$$\begin{aligned} & tk_0 a_T = [V_k^{(l)}(\alpha_1, \dots, \alpha_k, \dots, \alpha_l) = \alpha_k], \\ & \text{where } tk_0 \in Q; \text{ name } a_T, V_k^{(l)} \in S; \end{aligned} \tag{4}$$

The *generalized terminal characteristic* quantum $tk_1 b_T$ is described with a characteristic function χ_{Y_j} of a set Y_j for admissible values α_k^j of the j feature x_j :

$$tk_1 b_T = [\chi_{Y_j}(\alpha_k^j)] = \begin{cases} 1, & \text{if } \alpha_k^j \in Y_j, \\ 0, & \text{if } \alpha_k^j \notin Y_j, \end{cases} \quad k = (1, 2, \dots, r_j). \tag{5}$$

Definition 1. The different-level algorithmic structures, being received from terminal quantum $tk_1 y_T$ (3), $tk_0 a_T$ (4) and $tk_1 b_T$ (5) with a help of finite number of applying Π -operator, CON(•)-operator and CON[•]-operator, are called **different-level algorithmic tk-knowledge** or **tRAKZ-models** of knowledge in conditions of α -**indeterminacy**, which form a class of authentic tRAKZ-models M_t .

In Fig.1 a quantum area $B_t^{(3)}$ of tRAKZ-model of DMO is shown, being described by three features: x_1 with $r_1 = 2$ values from $X^1 = \{\alpha_1^1, \alpha_2^1\}$; x_2 with $r_2 = 4$ values from $X^2 = \{\alpha_1^2, \alpha_2^2, \alpha_3^2, \alpha_4^2\}$ and x_3 with $r_3 = 3$ values from the

set $X^3 = \{\alpha_1^3, \alpha_2^3, \alpha_3^3\}$.

Vector domains are separated with a semicolon «:» and meet the different-type features of DMO, and components of domains – for the features values so that i component of j domain should contain «1», if we observe i value of j feature, otherwise i component equals to «0». If every domain of a **quantum of the 1st level** contains strictly only one «1», it is called an **element** one, otherwise it is called – an **interval** vector quantum. The points A and B of the area $B_t^{(3)}$ are responsible for element vector tk-knowledge tk_1A and tk_2B :

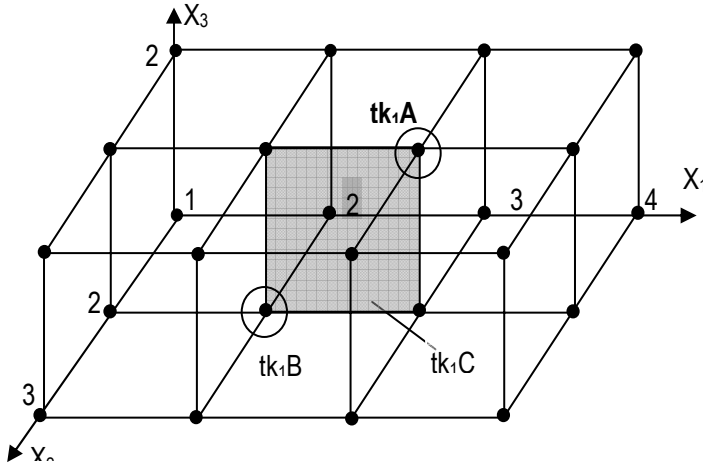


Fig.1. Area $B_t^{(3)}$ of tRAKZ-model

$$tk_1A = \begin{bmatrix} \overbrace{x_1}^{x_1} & \overbrace{x_2}^{x_2} & \overbrace{x_3}^{x_3} \\ 01:0010:010 \end{bmatrix}, \quad tk_1B = [10:0100:010], \quad (6)$$

The **interval C** $\subset B_t^{(3)}$ corresponds with an authentic **interval vector quantum of the 1st level**

$$tk_1C = [11:\overbrace{0110}^{x_2}:\overbrace{010}^{x_3}], \quad (7)$$

which can be represented by a **matrix t-quantum of the 2nd level tk₂C**, containing the joint 4 element vector t-quantum of the 1st level:

$$tk_2C = \begin{bmatrix} \overbrace{x_1}^{x_1} & \overbrace{x_2}^{x_2} & \overbrace{x_3}^{x_3} \\ 01:0010:010 \\ 10:0010:010 \\ 01:0100:010 \\ 10:0100:010 \end{bmatrix} \quad (8)$$

Besides, is t-quantum tk_1C (7) represents a conjunct, an elementary conjunction corresponds to it:

$$(x_1 \in \{\alpha_1^{(1)}, \alpha_2^{(1)}\}) \wedge (x_2 \in \{\alpha_2^{(2)}, \alpha_3^{(2)}\}) \wedge (x_3 \in \{\alpha_2^{(3)}\}) \quad (9)$$

The elementary conjunction (9) can be represented as a predicate equation:

$$((x_1 = \alpha_1^{(1)}) \vee (x_1 = \alpha_2^{(1)})) \wedge ((x_2 = \alpha_2^{(2)}) \vee (x_2 = \alpha_3^{(2)})) \wedge (x_3 = \alpha_2^{(3)}) = 1 \quad (10)$$

So, the class M_t of tRAKZ-models represents a set of *uniform quantum tools* for describing **implicative laws**, and also different **facts** to represent them in the three equivalent forms: *multiple* (points, intervals of area $B_t^{(n)}$); *vector-matrix* (domain structures); *analytic* (finite predicates).

3. Inductive search and deductive derivation of solutions as tk-knowledge

Under the **facts** we understand the *measured* DMO features of different type and their logical combinations, and also any *observed* events and situations, having relation to DMO and being represented by *knowledge quantum* of different levels, i.e. by **tRAKZ-models**. The tables of **empirical data** (TED) $T_o(m,n)$ are typical examples of real facts.

Under the laws (DMO are subordinated to them) we consider **implicative (forbidden) logical connections** between features of DMO, they are rather **stable** to be defined while analyzing a limited TED $T_0(m,n)$.

Definition 2. A **stable connection** between r characteristics of DMO from the general number of n , ($r \leq n$), expressing *inadmissibility* of at least one combination of their values on a set of **tk-knowledge**, is called an **implicative law** or a **prohibition of r rank**.

In **trAKZ**-method of decision-making the *inductive derivation of tk-knowledge* is used to build a general "world model" in a form of **BtkZ** as a range of *implicative laws* being found by *learning tk-knowledge*, represented in a form of TED.

The *deductive derivation* of **tk-knowledge** is necessary to receive partials *conclusions* for the *observed facts*, basing on the BtkZ.

3.1. Inductive derivation operator of implicative BtkZ (INDS-operator)

The *existence of implicative law* as some forbidden knowledge quantum of s -level $tk_s \bar{Y}$ from T_r , according to TED $T_0(m,N)$, ($s=1,2$), is defined by the *evaluation* of its *certainty*, satisfying the inequality

$$M_s\{m,N,r\} = \frac{N! \cdot 2^{r(1-m)} \cdot (2^r - 1)^m}{r!(N-r)!} \leq M_s^* \quad (11)$$

where the given **possible limit value (threshold)** of M_s^* [Sirodza, 1992] evaluation.

In a practical diapason of values m and N rank r_{max} turns out to be **small**. This allows defining all the **implicative laws** using a check for intervals «**forbiddances**» of a rank that is *not more than* r_{max} . The disjunctive union of all the found forbidden intervals as conjunctions of combinations of informative features of DMO forms an analytic (predicate) description of the *forbidden area*, corresponding BtkZ.

Definition 3. The algorithmic procedure

$$INDS(tk_2 \Sigma_0; AZ; tk_2 \bar{\Sigma}_{BM}) = tk_2 \Sigma_0 \frac{INDS}{AZ} \rightarrow tk_2 \bar{\Sigma}_{BM}, \quad (12)$$

implementing **inductive derivation** of non-odd **BtkZ** = $tk_2 \bar{\Sigma}_{BM}$ in a form of a set of **simple prohibitions** from the learning knowledge quantum $tk_2 \Sigma_0$ using the algorithm **AZ**, is called an **operator of inductive derivation of implicative tk-knowledge (INDS-operator)** [Sirodza, 1992].

Algorithm AZ

Input: TED in a form of quantum $tk_2 \Sigma_0$ of size $m \times n$, threshold $M_s^* = 10^{-2}$, maximal rank $r_{max} = 3$.

Output: minimized BtkZ = $tk_2 \bar{\Sigma}_{BM}$ as a system of simple forbidden quanta, i.e. that do not result one from another.

Steps:

1. according to r_{max} patterns of features prohibitions combinations are formed. For $r_{max} = 3$ there are 8 patterns: <000>, <001>, <010>, <011>, <100>, <101>, <110>, <111>. Forbidden combinations are searched between domains components, but not inside a domain.

2. In the cycle in $tk_2 \Sigma_0$ all the combinations of features values are taken as doubles, and then as triples, etc. till r_{max} . The non-found in $tk_2 \Sigma_0$ pattern combinations are added to $tk_2 \bar{\Sigma}_B$.

3. The formed quantum of prohibitions $tk_2 \bar{\Sigma}_B$ is *minimized* in BtkZ = $tk_2 \bar{\Sigma}_{BM}$ using operators of gluing, merging and compression.

Let's assume that in the result of step 2 in the algorithm AZ we got a quantum $tk_2 \bar{\Sigma}_B$. DMO is characterized by three features x_1, x_2, x_3 .

$$tk_2 \overline{\Sigma_B} = \begin{bmatrix} \overbrace{x_1} & \overbrace{x_2} & \overbrace{x_3} \\ 01- & -1- & -1-- \\ 01- & 0- & -1-- \\ -10- & 1- & ---0 \\ --- & 1- & ---0 \\ 1-- & -0- & --1- \\ 0-- & -0- & --1- \end{bmatrix}, \text{ where «-» defines «it is indifferent if it is 0 or 1».$$

3.1. Gluing ($xy \vee x\bar{y} = x$)

$$tk_2 \overline{\Sigma_B} = \begin{bmatrix} 01- & -1- & -1-- \\ 01- & 0- & -1-- \\ -10- & 1- & ---0 \\ --- & 1- & ---0 \\ \underline{1-- & -0- & --1-} \\ \underline{0-- & -0- & --1-} \end{bmatrix} \Rightarrow tk_2 \overline{\Sigma_{B1}} = \begin{bmatrix} 01- & -1- & -1-- \\ 01- & 0- & -1-- \\ -10- & 1- & ---0 \\ --- & 1- & ---0 \\ \underline{--- & -0- & --1-} \end{bmatrix}$$

3.2. Merging ($xy \vee x = x$)

$$tk_2 \overline{\Sigma_{B1}} = \begin{bmatrix} 01- & -1- & ---0 \\ 01- & 0- & -1-- \\ \underline{-10- & 1- & ---0} \\ \underline{--- & 1- & ---0} \\ --- & -0- & --1- \end{bmatrix} \Rightarrow tk_2 \overline{\Sigma_{B2}} = \begin{bmatrix} 01- & -1- & -1-- \\ 01- & 0- & -1-- \\ \underline{--- & 1- & ---0} \\ --- & -0- & --1- \end{bmatrix}$$

3.3. Compression (union of quanta different with one domain only)

$$tk_2 \overline{\Sigma_{B2}} = \begin{bmatrix} \underline{01- & -1- & -1--} \\ \underline{01- & 0- & -1--} \\ --- & 1- & ---0 \\ --- & -0- & --1- \end{bmatrix} \Rightarrow tk_2 \overline{\Sigma_{BM}} = \begin{bmatrix} \underline{01- & 01- & -1--} \\ --- & 1- & ---0 \\ --- & -0- & --1- \end{bmatrix}$$

After steps 3.1-3.3 under the whole forbidden quantum database we get the searched minimized implicative $BtkZ = tk_2 \overline{\Sigma_{BM}}$.

3.2. Deductive derivation operator of decisions from implicative tk-knowledge.

It is necessary to solve the task of building the algorithm AL, implementing *deductive operating process* to search the *needed* decisions being correspondent with the *logical consequence* $tk_2 \|Y\|, tk_1 Y, tk_0 \beta_{ik}^{(j)}$:

$$tk_2 \overline{\Sigma_{BM}} \xrightarrow[ALI]{DED} tk_2 \|Y\|, \quad tk_2 \overline{\Sigma_{BM}} \xrightarrow[AL3]{DED} tk_1 Y, \quad tk_2 \overline{\Sigma_{BM}} \xrightarrow[AL2]{DED} tk_0 \beta_{ik}^{(j)}, \tag{13}$$

where $tk_2 \overline{\Sigma_{BM}}$ is a known database of *implicative tk-knowledge*.

The searched sequences $tk_2 \|Y\|, tk_1 Y, tk_0 \beta_{ik}^{(j)}$ (13) represent the different-level tk-knowledge, characterizing the decisions being made in basic tasks B_t and C_t according to the observed results.

Let a base of implicative tk-knowledge $tk_2 \overline{\Sigma_{BM}}$ is given and a quantum $tk_1 Y_\omega$ of knowledge about the *observed* DMO $\omega \in \Omega$ of a data domain being investigated. The **algorithm AL** to evaluate the *possible condition of DMO ω* according to *quanta of observations* $tk_1 Y_\omega$, based on a *known BtkZ*, is a implementation of *deductive derivation* for the searched decision according to the scheme (13). Let's note that under the possible condition of DMO ω we understand a *class* or *pattern* and the DMO ω is concerned to it while solving the B_t -task or a *category (value)* of prognosis connected with DMO ω if we solve the C_t -task.

Algorithm AL

Input: tk-knowledge $BtkZ = tk_2 \overline{\Sigma_{BM}}$ and observations $tk_1 Y_\omega$ for DMO ω .

Output: deductively derived tk-knowledge $tk_2 \|\overline{Y_\omega^*}\|$ from **BtkZ** about the possible condition of DMO ω , according to the observations $tk_1 Y_\omega$.

Steps:

1. To make a substitution of quantum values $tk_1 Y_\omega$ in **BtkZ**= $tk_2 \overline{\Sigma_{BM}}$ in this way: to delete columns in a matrix quantum $tk_2 \overline{\Sigma_{BM}}$, meeting the features of the observed quantum $tk_1 Y_\omega$.
2. To delete the rows, which are orthogonal to the observation $tk_1 Y_\omega$ row, from the formed minor (respectively to the known features; 'orthogonal' means those having opposite in the meaning). In such a way we get $tk_2 \|\overline{Y_\omega^*}\|$.
3. To invert the received quantum and consider it to be the result $tk_2 \overline{\Sigma_\omega^*} = tk_2 \|\overline{Y_\omega^*}\|$.

The algorithm is analogical for deriving the logical sequences $tk_1 Y$, $tk_0 \beta_{ik}^{(j)}$ [Sirodza, 2002].

Let's assume the DMO is characterized with 4 features (x_1, x_2, x_3, x_4), and the BtkZ has been inductively received in a form of:

$$tk_2 \overline{\Sigma_{BM}} = \begin{bmatrix} \overbrace{01}^{x_1} - : \overbrace{-1}^{x_2} : \overbrace{-1}^{x_3} - - - : \overbrace{01}^{x_4} \\ 01 - : 0 - : -1 - - - : 1 - \\ -10 : 1 - : - - - 0 : 1 - \\ - - - : 1 - : - - - 0 : 0 - \\ 1 - - : -0 : - - 1 - : -0 \\ 0 - - : -0 : - - 1 - : -1 \end{bmatrix}$$

There is also a quantum to observe the DMO $tk_1 Y_\omega = [001:10:0100:--]$. It is required to define the possible value of the non-measured feature x_4 . According to the algorithm steps we get:

$$tk_1 Y_\omega = [\quad 001 : 10 : 0100 : -- \quad]$$

$$tk_2 \overline{\Sigma_{BM}} = \begin{bmatrix} 01 - : \mathbf{-1} : -1 - - : 01 \\ 01 - : \mathbf{0-} : -1 - - : 1- \\ \mathbf{-10} : 1- : - - - 0 : 1- \\ - - - : 1- : - - - 0 : 0- \\ \mathbf{1- -} : -0 : - - 1- : -0 \\ 0 - - : -0 : \mathbf{- - 1-} : -1 \end{bmatrix} \Rightarrow \begin{bmatrix} 01 : 1 : 1 : 01 \\ 01 : 0 : 1 : 1 \\ -10 : 1- : - - - 0 : 1- \\ \mathbf{- - - : 1- : - - - 0 : 0-} \\ 1- - : -0 : - - 1- : -0 \\ 0 - - : -0 : - - 1- : -1 \end{bmatrix}$$

After applying algorithm AL steps 1,2 a quantum $[- - : 1- : - - 0 : 0-]$ is left. After the inversion (step 3 of the algorithm AL) $tk_0 \beta_{ik}^{(j)} = [1]$, i.e. the 4th feature (the 4th domain corresponds to it) takes the first value. Analogically the tasks to prognosis the several features values are being solved. In such a way the B_{τ} , C_{τ} -tasks have been solved with a help of the algorithm AL.

Conclusion

Operating derivation of identification and prognostic decisions using tRAKZ-method suppose such a sequence of *operating* transformations of *different-level tk-knowledge*: using **induction operator** according to the given **table of empirical data** (TED) as learning tk-knowledge the **database of authentic knowledge quanta** (BtkZ) is synthesized. Then using **deduction operator** according to the observed (*input*) tk-knowledge of DMO, the searched *identification* or *prognostic* decisions are derived on the basis of BtkZ in a form of *resulting tk-knowledge*.

Operating method of decision derivation is based on the computer manipulation of vector-matrix structures (unlike the existing methods), that allows to abbreviate the time for BtkZ synthesis as a conclusive rule and to increase the efficiency of computer decision-making.

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CONSTRUCTING OF A CONSENSUS OF SEVERAL EXPERTS STATEMENTS*

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Abstract: Let Γ be a population of elements or objects concerned by the problem of recognition. By assumption, some experts give probabilistic predictions of unknown belonging classes γ of objects $a \in \Gamma$, being already aware of their description $X(a)$. In this paper, we present a method of aggregating sets of individual statements into a collective one using distances / similarities between multidimensional sets in heterogeneous feature space.

Keywords: pattern recognition, distance between experts statements, consensus.

ACM Classification Keywords: I.2.6. Artificial Intelligence - knowledge acquisition.

Introduction

We assume that $X(a) = (X_1(a), \dots, X_j(a), \dots, X_n(a))$, where the set X may simultaneously contain qualitative and quantitative features X_j , $j = \overline{1, n}$. Let D_j be the domain of the feature X_j , $j = \overline{1, n}$. The feature space is given by the product set $D = \prod_{j=1}^n D_j$. In this paper, we consider statements S^i , $i = \overline{1, M}$; represented as sentences of type "if $X(a) \in E^i$, then the object a belongs to the γ -th pattern with probability p^i ", where $\gamma \in \{1, \dots, k\}$, $E^i = \prod_{j=1}^n E_j^i$, $E_j^i \subseteq D_j$, $E_j^i = [\alpha_j^i, \beta_j^i]$ if X_j is a quantitative feature, E_j^i is a finite subset of feature values if X_j is a nominal feature. By assumption, each statement S^i has its own weight w^i . Such a value is like a measure of "assurance".

Without loss of generality, we can limit our discussion to the case of two classes, $k = 2$.

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