# SELFSTRUCTURIZED SYSTEMS[1]

**Victor Gladun, Vitalii Velychko, Yurii Ivaskiv**

***Abstract***: *The problems of constructing the selfsrtucturized systems of memory of intelligence information processing tools, allowing formation of associative links in the memory, hierarchical organization and classification, generating concepts in the process of the information input, are discussed. The principles and methods for realization of selfstructurized systems on basis of hierarchic network structures of some special class – growing pyramidal network are studied. The algorithms for building, learning and recognition on basis of such type network structures are proposed. The examples of practical application are demonstrated.*

***Keywords***: *knowledge discovery, classification, prediction, growing pyramidal networks, concept formation.*

***ACM Classification Keywords***: *I.2.4 Knowledge Representation Formalisms and Methods - Semantic networks, F.1.1 Models of Computation - Self-modifying machines (e.g., neural networks)*

## Introduction

The task of constructing the self structurized systems is considered in context with intellectualization of the information processing tools. Selfstructurization provides a possibility of changing the structure of data, stored in memory, in the process of the tools functioning as a result of interaction between the received and already stored information. Systems in which the perception of new

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information is accompanied by simultaneous structurization of the information stored in memory, we shall name hereinafter selfstructurized.

Development of principles and methods of constructing the selfstructurized systems in many respects defines a possibility of intellectualization of the information processing tools. Adaptability to the task, being solved, has to do with changing the structure of data. As a result, the possibility of searching in the memory focused on storage of complex data of the large volume occurs, which allows increasing productivity of the used tools, raise accuracy and reliability of received results.

Main processes of structurization of the perceived information consist in formation of semantic and syntactic links among objects by separation of crossings of their attributive representations, as well as the generalized logic attributive models of classes of objects - concepts. As a result of these processes realization, the semantic and syntactic similarity of the perceived information with the stored information is established. Detected associations are fixed as structural changes in memory.

Following basic requirements to data structures in the intellectual systems are set for the decision of such tasks as regularity discovery, classification, forecasting, diagnostics [1]:

The structure of the data should be the multiple-parameter model, reflecting significant properties of researched object. It should provide a possibility to account for the simultaneous influence on researched factor of various combinations of known properties of the researched object.

The model of the researched object should minimize scanning of large-scale data: along with growth of data size, the time of performing of the choice operations grows. It interferes with application of some analysis methods. The model also should be applicable for verification and interpretation.

It should be noted, that in solving tasks of diagnostics and forecasting the models characterized by higher level of generalization of models of classes of objects have advantage. The logic expressions describing such models turn out easier if the complexity is evaluated by number of variables. Simplification of logic expressions results in simple structure of memory and, therefore, simplifies the process of structurization.

In knowledge representation in intelligent systems, those network structures have advantages, which have some information units in vertices, and arches describing links among them. In similar systems, the elements of knowledge representation are combined in the hierarchical structure, realizing such functions, as formation of links among attributive presentations of researched object by allocation of their crossings, hierarchical ordering, classification, concepts formation. In selfstructurized systems, such functions should be performed in the process of the information perceiving.

Condition of an element formation of network structure, for example, unit or link between units, is some relation between determined structural elements of a network. The relations determining formation of structure elements of selfstrtucturized systems we call structurized.

There are two basic ways of objects representation in the information processing systems: by name (condensed) or by sets of attribute values (expanded). The memory structures in selfstrtucturized systems and the appropriate network structures should provide bidirectional conversion between such representations.

Building of selfstrtucturized systems is proposed to be realized on basis of network with hierarchical structures, named as growing pyramidal networks (GPN) [5].

The theory as well as practical application of GPN is expounded in a number of publications [3-6]. GPN realization has following stages:

– to construct the structure of a network for some initial set of objects, assigned by attributive descriptions,

– to train the structure, with a purpose to allocate its elements, allowing to classify all objects of the initial set,

– to recognize belonging to some class of objects of certain object, which is not belonging to initial set of objects.

The mechanisms, providing conversion between converged representation of objects and representation as a set of attributes values in human neurosystem, are discussed in the article [2]. The present work illustrates recent versions of algorithms for building and training GPN, as well as examples of their application.

## Building of GPN

A *growing pyramidal network* is an acyclic oriented graph having no vertexes with a single incoming arc. Examples of the pyramidal networks are shown in Figs.1,2,3. Vertices having no incoming arcs are referred to as *receptors*. Other vertices are called *conceptors*. The subgraph of the pyramidal network that contains vertex *a* and all the vertices from which there are paths to vertex *a* is called the *pyramid* of vertex *a*. The set of vertices contained in the pyramid of vertex *a* is referred to as the *subset* of vertex *a*. The set of vertices reachable by paths from vertex *a* is called the *superset* of vertex *a*. The set of vertex, having paths from vertex *a*, is referred to its *superset.*

In *subset* and *superset* of the vertex, 0-*subset* and 0-*superset* are allocated, consisting of those vertices, which are connected to it directly. When the network is building, the input information is represented by sets of attributes values describing some objects (materials, states of the equipment, a situation, illness etc.). Receptors correspond to values of attributes. In various tasks, they can be represented by names of properties, relations, states, actions, objects or classes of objects. Conceptors correspond to descriptions of objects in general and to crossings of descriptions and represent GPN vertices.

Initially the network consists only of receptors. Conceptors are formed as a result of algorithm of construction of a network. After input of object attribute description, corresponding receptors switch to a *state of excitation*. The process of excitation propagates through the network. A conceptor switches into the state of excitation if all vertices of its 0-subset are excited. Receptors and conceptors retain their state of excitation during all operations of network building.

Let $F_a$ be the subset of excited vertices of the 0-subset of vertex *a*; *G* be the set of excited vertices in the network that do not have other excited vertices in their supersets. New vertices are added to the network by the following two rules:

**Rule A1**. If vertex *a*, that is a conceptor, is not excited and the power of set $F_a$ exceeds 1, then the arcs joining vertices of set $F_a$ with the vertex *a* are liquidated and a new conceptor is added to the network which is joined with vertices of set $F_a$ by incoming arcs and with the vertex *a* by an outgoing arc.

The new vertex is in the state of excitation. Rule A1 is illustrated in Fig.1 (a,b). According to the Rule A1, the condition for adding a new vertex to the network is a situation, when certain network vertex is not completely excited (at least two vertices of 0-subset are excited). Fig. 1.a shows a fragment of network in some initial state. Receptors 4,5 switch to a state of excitation, the network switches to state Fig. 1.b, a new vertex appears – a new conceptor. Receptors 2,3 switch to a state of excitation additionally. The network switches to state Fig. 1.c.

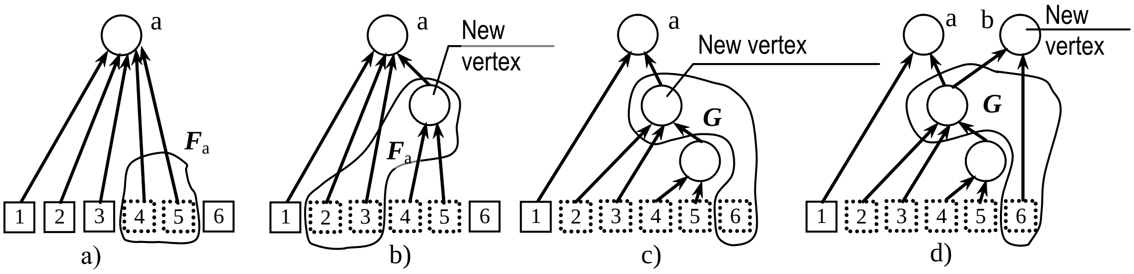


Fig. 1.

New vertices are inserted in 0-subset of vertices, which are not completely excited. New vertices correspond to intersection of object descriptions, represented by incoming arches. Once new vertices have been introduced into all network sections where the condition of rule A1 is satisfied, rule A2 is applied to the obtained network fragment, concluding the object pyramid building.

**Rule A2**. If the power of set *G* exceeds 1 element, a new conceptor is added to the network, which is joined with all vertices of set *G* by incoming arcs.

The new vertex is in the state of excitation. Rule A2 is illustrated in Fig.1c,d. Network Fig1.d was obtained after the excitation of receptors 2-6.

In applying the Rule A1 the main cross-linking relation is a relation of intersection of receptor set, excited by input of the object description and other sets of receptors included into pyramid, recently formed by conceptors. Rule A2 concludes the building of pyramid, which represents complete description of the introduced object.

Pyramidal networks are convenient for execution of various operations of associative search.

For example, it is possible to select all the objects that contain a given combination of attribute values by tracing the paths that outgo from the network vertex corresponding to this combination. To select all the objects whose descriptions intersect with the description of a given object it is necessary to trace the paths that outgo from vertices of its pyramid. Rules A1, A2 establishes associative proximity between objects having common combinations of attribute values.

Hierarchical organization is an important property of pyramidal networks. This provides a natural way for reflecting the structure of complex objects and generic-species interconnections.

Conceptors of the network correspond to combinations of attribute values that define separate objects and conjunctive classes of objects. By introducing the excited vertices into the object pyramid, the object is referred to classes, which descriptions are represented by these vertices. Thus, during the network building the conjunctive classes of objects are formed, the classification of objects is performed without a teacher. Classifying properties of pyramid network are vital for modeling environments and situations.

Conversion from converged representation of objects (conceptors) to expanded (sets of receptors) is performed by scanning pyramids in top-down and down-top directions.

## Training GPN

Training GPN consists in formation of the structures representing concepts, on a basis of attributive descriptions of the objects incorporated into classes with known properties.

Concept is an element of knowledge system, representing generalized logic attributive model of a class of objects, by which processes of recognition of objects are realized. The set of objects generalized in concept is its *volume*.

Consider a task of inductive formation of concepts for not intersected sets of objects $V_1, V_2, \ldots, V_n$ , each set represents some class of objects with known properties. Let $L$ - be a set of objects used as training set. All the objects of set $L$ are represented by sets of attribute values. Relations $L \cap V_i \neq \varnothing$ and $V_i \not\subset L(i = 1,2,\ldots,n)$ are set. Each object from set $L$ corresponds to one set $V_i$. It is necessary to generate *n* concepts by analysis *L*. The amount of these concepts must be sufficient for correct recognition of belongings of anyone $l \in L$ to one of sets $V_i$.

Each concept, generated on the basis of training set, is approximation to real concept, the proximity of concepts depends on representativeness of training set, i.e. on the detalization of peculiarities of the concept volume.

In forming the concept corresponding to set $V_i$ , the objects of training set included in $V_i$**,** are considered as examples of set $V_i$ , and the objects, not included in $V_i$ , - as counterexamples of set $V_i$**.**

The combinations of attributes allocated in building of a pyramidal network, representing descriptions of objects of training set, are used as "a building material", a basis of further logic structure of concept.

Let *L* be the pyramidal network representing all of training set objects. For formation of concepts $A_1, A_2, \ldots, A_n$, corresponding to sets $V_1, V_2, \ldots, V_n$, pyramids of all objects of training set are scanned in order. The vertices of scanned pyramid during its scanning are considered excited. Special vertices in network are identified in order to recognize objects from the concept volume. They are referred to as *check vertices* of a certain concept. In selecting the check vertexes, two characteristics of network vertexes are used: $\{m_1, m_2, \ldots, m_n\}$, where $m_i\ (i = 1,2,\ldots,n)$ is a number of objects of volume of concept $A_i$ , which pyramids include the given vertex; and *k*, which is the number of receptors in the pyramid of this vertex. For receptors *k*=1. While scanning, the pyramid is transformed by the following rules.

**Rule B1.** If in the pyramid of an object from concept volume $A_i$, the vertex, having the largest $k$ among all the vertices with the largest $m_i$, is not a check vertex of concept $A_i$, then it is marked as a check vertex of the concept $A_i$.

The rule allows existence several vertexes among the excited vertexes with identical $m_i$, exceeding $m_i$ of other excited vertexes. If in group of the vertexes having largest $m_i$, values $k$ of all vertexes are equal, any of vertexes can be marked as check vertex of concept $A_i$.

The rule B1 is illustrated in Fig. 2. In a situation demonstrated by Fig. 2, in excitation in pyramid of vertex 2 vertex 6 is selected as check vertex as having the largest $k$ among vertices with the largest $m_i$ (6, 13, 14). Values $m_i$ are shown inside symbols of vertices.

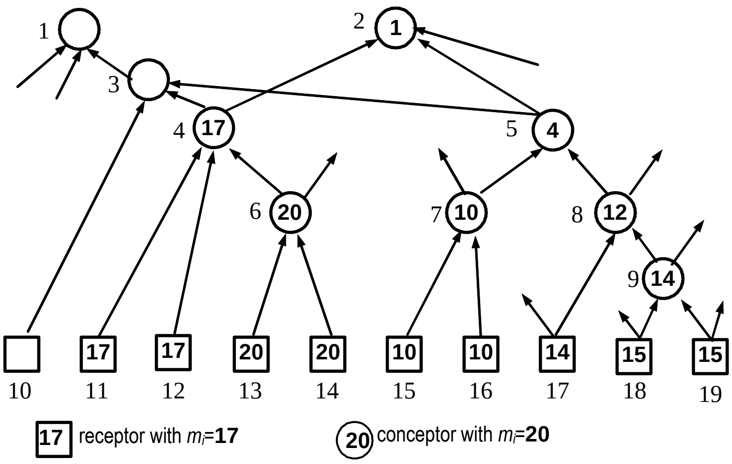


Fig. 2.

**Rule B2**. If the pyramid of an object from concept volume $A_i$ contains check vertices of other concepts whose supersets do not contain excited check vertices of concept $A_i$, then in each of these supersets the vertex, having the largest $k$ among all excited vertices with the largest $m_i$, is marked as a check vertex of concept $A_{i.}$

According to this rule the excitation of the pyramid of vertex 2 (Fig.3.a) on the condition, that it represents an objects from concept volume $A_i$, results in choosing vertex 5 as the check vertex of concept $A_i$ (Fig. 3.b).

By check vertexes we select the most typical (having the largest $m_i$) combinations of attribute values, belonging to objects from concept volume. For example, selecting the vertex 8 (Fig 3a.) as a check vertex means selection of combination of value attributes, corresponding to receptors 17,18,19.

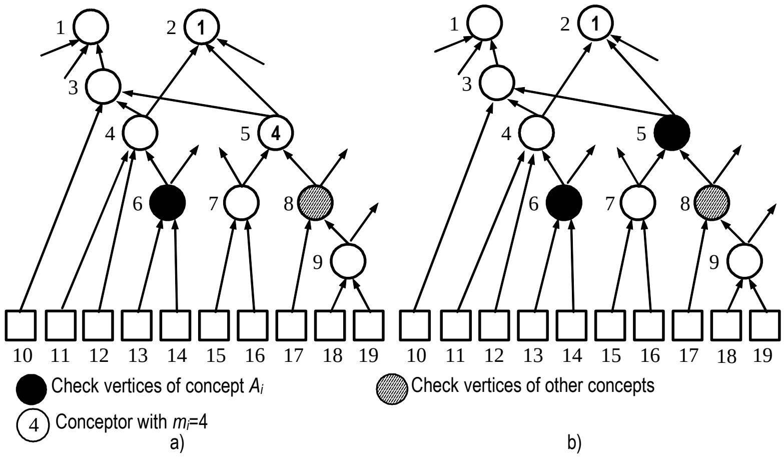


Fig. 3.

If at least one new check vertex appears while scanning objects of the training set, i.e. conditions of Rules B1 or B2 have been performed once at least, the training set is rescanned. The algorithm stops if during the scanning of the training set no new check vertex appears.

## Recognition on basis of GPN

The task of recognition is based on the following rule.

Certain object belongs to the concept volume $A_i$ if its pyramid has check vertexes $A_i$ and does not contain check vertices of any other concept not having excited check vertices of concept $A_i$ concept in their supersets. If this condition does not hold for any of the concepts, the object is referred to as unrecognized.

The execution time of the above algorithm is always finite. If the volumes of the formed concepts $V_1,V_2,...,V_i,...,V_n$ do not intersect, than after execution the algorithm the recognition rule completely divides the training set into subsets $L_i = V_i \cap L(i = 1..n)$.

The formed concepts are represented in the network as ensembles of check vertexes.

There is an algorithm of composing the logic descriptions of concepts, formed in the network as a result of the training process, described above. The formed logical expression contains logical relations, represented by allocation of check vertexes, describing the concepts in the network, defining different classes of objects.

The analytical tasks, such as diagnostics or prognosis, can be reduced to the task of classification, i.e. to belongings the research object to a class of objects, with a property characteristic or a set of properties significant for diagnostics of prognosis.

## GPN Application

The following example illustrates the result of concepts formation on the basis of the analysis of a fragment of training set shown in the table 1.

The table has descriptions of ceramic materials of two classes with the following attributes: M - material, T - fineness of powder, C - mix proportion, PP – powder manufacturing method, GP - conditions of obtaining the sample at hot pressing, NoGP - conditions of obtaining the sample without hot pressing, DU - special conditions of manufacturing of a sample, Por - porosity, Z - granularity.

Letters and figures in sections specify values of the appropriate attributes.

Fig. 4 demonstrates the appropriate pyramidal network with the formed concepts. Check vertices PP_SYN, Por_3, 239, 163 characterize class 1, check vertexes 158, 308 and $7 characterize class 2.

The class 1 is described by the following logical expression, where ∨, ∧, ¬ - logical operations of a disjunction, conjunction and negation:

PP_SYN ∧ ¬{T_1 ∧ GP_1} ∧ ¬{M_ZrB ∧ C_ZrO-C ∧ T_11 ∧ NoGP_9 ∧ Z_2} ∨
Por_3 ∧ ¬{T_8 ∧ Z_6 ∧ M_TiB ∧ C_TiO-C ∧ PP_KRB ∧ GP_3} ∨
M_ZrB ∧ C_ZrO-C ∧ T_11 ∧ PP_SYN ∧ NoGP_9 ∧ Por_3 ∧ Z_2 ∨
M_1AlO ∧ T_1 ∧ C_AlO ∧ PP_SYN ∧ GP_1 ∧ Por_4.

Table 1. Training set.

| Object | Class | M | T | C | PP | GP | NoGP | DU | Por | Z |
|---|---|---|---|---|---|---|---|---|---|---|
| 97 | 1 | Al | 2 | | SYN | 2 | | 2GP | | |
| 96 | 1 | Al | 2 | | SYN | 2 | | 1GP | | |
| 92 | 1 | Al | 2 | | SYN | 2 | | 2GP | 1 | |
| 227 | 1 | TiB | 11 | TiO-C | SYN | | 9 | | 3 | 2 |
| 228 | 1 | TiB | 11 | TiO-C | SYN | | 9 | | 3 | 2 |
| 229 | 1 | TiB | 11 | TiO-C | SYN | | 9 | | 3 | 2 |
| 233 | 1 | SiC | 11 | TiO-C | SYN | | 9 | | 3 | 2 |
| 234 | 1 | SiC | 11 | SiO-C | SYN | | 9 | | 3 | 2 |
| 235 | 1 | SiC | 11 | SiO-C | SYN | | 9 | | 3 | 2 |
| 237 | 1 | SiC | 11 | SiO-C | SYN | | 9 | | 3 | 2 |
| 239 | 1 | ZrB | 11 | ZrO-C | SYN | | 9 | | 3 | 2 |
| 240 | 1 | ZrB | 11 | ZrO-C | SYN | | 9 | | 3 | 2 |
| 241 | 1 | ZrB | 11 | ZrO-C | SYN | | 9 | | 3 | 2 |
| 242 | 1 | ZrB | 11 | ZrO-C | SYN | | 9 | | 3 | 2 |
| 154 | 1 | TiB | 7 | TiO-C | KRB | 3 | | | 3 | 4 |
| 156 | 1 | TiB | 7 | TiO-C | KRB | 3 | | | 3 | 4 |
| 163 | 1 | 1AlO | 1 | AlO | SYN | 1 | | | 4 | |
| 158 | 2 | TiB | 8 | TiO-C | KRB | 3 | | | 3 | 6 |
| 160 | 2 | 1AlO | 1 | AlO | SYN | 1 | | | 1 | |
| 159 | 2 | BC | 1 | | SYN | 1 | | | 1 | |
| 308 | 2 | ZrB | 11 | ZrO-C | SYN | | 9 | | | 2 |

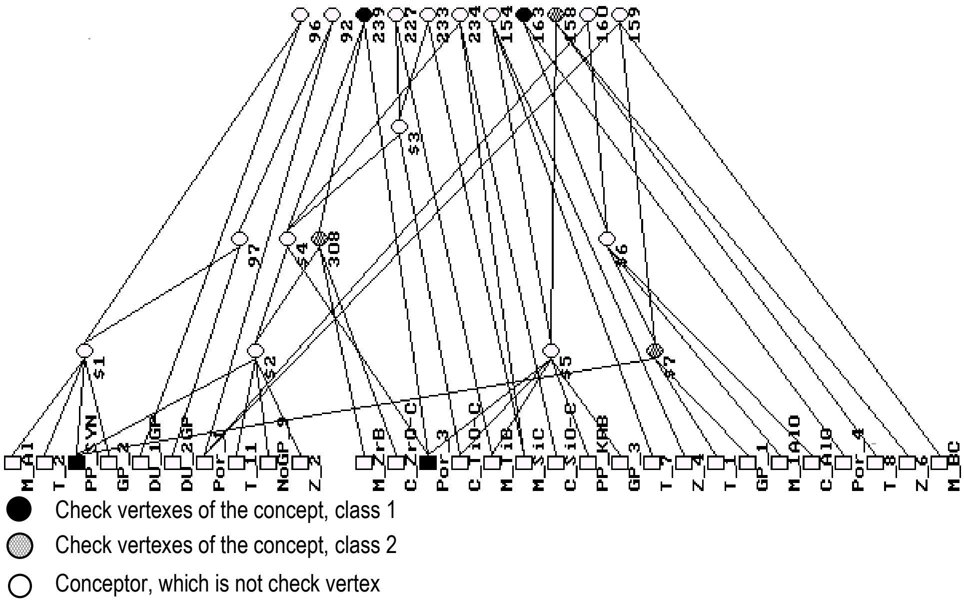


Fig 4.

The logic expressions, defining various classes of objects, are united in *cluster databases* (CDB). CDB contain the information on groups of objects (clusters), specific to the area of study. On basis CDB problems of classification, diagnostics and forecasting are solved. After the concept for some class of objects has been formed, problems of forecasting and diagnostics are reduced to a problem of classification. Classification of new objects is performed by comparing the attribute descriptions with the concept, defining a class of predictable or diagnosing objects. Objects can be classified by evaluating the value of the logical expressions that represent corresponding concepts. The variables, corresponding to the attribute values of the recognized object, set 1, other variable set 0. If the entire expression takes the value 1, that means that the object is included into volume of concept.

The next geometric interpretation of the concept formation algorithm can be proposed.

Every network vertex, having $k$ receptors in its subset, corresponds to $(s-k)$-dimensional plane in $s$-dimensional attribute space. The plane contains all the points corresponding to objects whose perceiving results in exiting of this vertex. $(s-k)$-dimensional planes corresponding to check vertices of concept $A_i$ are referred to as *zones* of concept $A_i$.

The following statements are true for growing pyramidal networks.

**Statement 1.** The zone of any network vertex is totally included in zones of its subset vertices and totally includes all zones of its superset vertices.

**Statement 2.** The point corresponding to an object in the attribute space is located inside an intersection of zones of those check vertices, which are exited when the object is perceived.

Point $a$ corresponding to the object in the attribute space is directly included in the zone $Z$ of concept $A_i$ if there is no other zones of this concept which include point $a$ and totally are included in zone $Z$.

The geometric interpretation of the above-described rules for concept formation algorithm is as follows.

**Rule B1.** For every object of concept volume $A_i$ $(s-k)$-dimensional plane of the exited vertex having the highest $k$ among all the vertices with the highest $m_i$ becomes the zone of concept $A_i$.

**Rule B2.** If the point, corresponding to an object of concept volume $A_i$ in the attribute space, is directly included in zones of the other concepts, then a zone of concept $A_i$ is created inside each of those zones.

The algorithm of concept formation stops, when during regular examination of the training set, points corresponding to objects from any class are not directly included in zones of the other concepts. When learning is finished, an object corresponds to concept volume $A_i$ if the appropriate point in the attribute space is directly included in at least one zone of concept $A_i$ and is not included in any zone of the other concepts.

Zones of concept $A_i$ , directly inclusive points of objects, corresponding to objects from its volume, as well as points, corresponding to objects from different concepts, are referred to as *boundary zones* of concept $A_i$ .

**Statement 3.** According to Rule B2 new zones can be created only directly inside boundary zones.

Formation of new zones inside boundary zones results in division of boundary zones.

Construction of approximating region for concept $A_i$ consists of two processes: rough covering with concept $A_i$ *i* zones the distribution domain of training set objects corresponding to concept $A_i$ (Rule B1); and division of arising boundary zones (Rule B2).

On the basis of geometrical interpretation, algorithm convergence can have the following explanation.

For each concept the total covering by zones of allocation area of the training set objects, which are included in its volume, results in scanning of all objects, i.e. during single scanning of training set. The boundary zones include points of objects of training set, for which conditions of Rule B2 work. Therefore in every scanning of training set the division of all boundary zones, formed by previous scanning, occurs.

Process of division of boundary zones proceeds, as long as boundary zones exist, and can result in allocation of separate points of attribute space as zones. As number of the points corresponding to objects of training set is finite in each boundary zone, the process of division of boundary zones is finite too.

Absence of boundary zones after the termination of process of division means, that each of concepts in attribute space has area containing all points, corresponding objects of training set which are included in concept volume, and not including any point corresponding to other objects of training set. Thus, after the termination of division of boundary zones total division of training set into subsets $H_i = V_i \cap H(i = 1,2,...,n)$ occurs. As a result algorithm operation for each of the formed concepts, the area is composed of zones of attribute space. This area contains all points of objects of the appropriate class and does not contain any point corresponding to objects of other classes. This area approximates allocation area of objects of the corresponding class. As the approximating area consists of linear elementary areas (hyperplanes), its limiting surface is piecewise-linear. Therefore, the algorithm performs the piecewise-linear division of objects, which correspond to different concepts.

The described method provides decisions of analytical problems of classification, diagnostics and forecasting on the basis of logic models of objects classes. The model displays dependences of an investigated class on combinations of values of attributes, i.e. allows taking account for combined influence of several attributes.

An important distinction of a method of concepts formation in growing pyramidal networks is the possibility to introduce in concepts the so-called excluding attributes which do not correspond to objects of a researched class. As a result, the formed concepts have more compact logic structure, which allows increasing the accuracy of diagnosis or forecasting. In logic expression the excluding attributes are presented by variables with negation.

All search operations in growing pyramidal network are limited to rather small fragment of a network, which includes an object pyramid and vertices directly linked to it. As a result, we have a possibility solve practical analytical problems based on large-scale data.

In a pyramidal network the information is stored by its representation in structure of network. Rules A1-A2, B1-B2 define the rules of memory organization while new information perception. The information of objects and classes of objects is presented by ensembles of vertices (pyramids), allocated in all network. Incoming of the new information causes redistribution of links among vertices of network, i.e. modifying of its structure.

The advantages of growing pyramidal networks become obvious in implementation, which allows parallel distribution of signals in network. The important property of a network as means of information storage is that the possibility of parallel distribution of signals is combined with parallel reception of signals to receptors.

Despite of the certain similarity of the processes proceeding in GPN and neural networks there some distinctions in operating. Main distinction of GPN is that its structure is formed depending on the input data automatically. The adaptation of network structure to the structure of data results in optimization of the information representation. In addition, in contrast to neural networks, the adaptation does not require the introduction of aprioristic redundancy of a network, and training process does not depend on the predetermined configuration of a network. The weakness of neural networks comparing with GPN is that the allocated generalized knowledge cannot be explicitly represented as rules or logic expression. It complicates their understanding by person.

Various set-theoretic descriptions of GPN are given in [4,5]. The [5] considers the so-called β–pyramidal networks (β-PN) modification of GPN for the ranked data. β-PN are useful for data presentation in problems of management, taking and planning decisions (for example, in planning the actions of robots), and also in semantic analysis and synthesis of natural-language texts. In [3-5] the algorithm of formation of concepts in GPN for nondetermined learning process, i.e. for a case when crossing volumes of different concepts occurs, is considered.

The program complex used for experimentation and solving the applied tasks using GPN [8], includes systems CONFOR, realizing processes of building and training GPN, and DISCRET by which the attributes given in numerical scales, are transformed in nominal scales. Discretization of attributes is performed on numerical scales by analysis of distributions of training set objects belonging to different classes.

Typical application fields for GPN are as follows: forecasting of new chemical compounds and materials with the predefined properties[7-9], forecasting in genetics, geology, the solar activity forecasting, medical and technical diagnostics, the robot planning, forecasting of failures of complex units etc. As an example we offer tasks of inorganic compounds forecasting with predefined properties. The tables containing attribute descriptions of binary, ternary and quaternary systems of chemical elements, forming or not forming the chemical compounds were used as training set. Training sets for binary, ternary and quaternary systems included 1333, 4278 and 4963 descriptions, and test set - 692, 2156 and 2536 descriptions. Each chemical element was described by the set of 87 attribute values. Descriptions of binary, ternary and quaternary systems had 174, 261 and 348 attributes. The recognition furnished the 99% accuracy result.

## Conclusion

The growing pyramidal network is the network memory self-adapting to the structure of incoming information. In selfstructurized systems the structure of data adapts to the task (classes of objects are allocated and defined) which results in optimization of the solution. In contrast to neural networks, the adaptation does not require the introduction of aprioristic redundancy of a network. In GPN various combinations of the assigned initial properties are formed, which increase the accuracy of analytical tasks solving. Selfstructurized systems allow not only to locate the dependences providing the diagnosis or the forecasting but also to create their logic descriptions.

The researches, operating on complex large-scale data, have shown high efficiency in applying the growing pyramidal networks for solving the analytical tasks. Such properties as simplicity of modification, combining the input of information with classification, generalization and allocation of essential attributes, high associativity, all make the growing pyramidal networks an indispensable component of intellectual systems.

## Bibliography


1. Pospelov D.A. Logic-linguistic models in control systems. -Moscow: Energoizdat.-1981.
2. Voronkov G.V., Rabinovich Z.L. Natural environment of memory and thinking: modelling representation. Proceedings of international conference. "Knowledge - Dialogue-Solution"-2001.-SPb.-2001.
3. Gladun V.P. Partnership with computer. Man-Computer Purposeful Systems.-Kiev: Port-Royal. - 2000.
4. V.P.Gladun. Processes of New Knowledge Formation. Sofia: SD Pedagog, 1994, 192 p.
5. V.P.Gladun. Planning of Solutions. Kiev: Naukova Dumka. 1987. 168 p.
6. Gladun V.P. and Vashchenko N.D. Analytical processes in pyramidal networks // Intern. Journal on Information Theories and Applications. FOI-COMMERCE, Sofia.-2000.-Vol.7, - №3.
7. Kiselyova N., Gladun V., Vashchenko N. Computational Materials Design Using Artificial Intelligence Methods. Journal of Alloys and Compounds. 279 (1998), pp. 8-13.
8. www.aduis.com.ua <http: // www.aduis.com.ua>
9. Kiseleva N.N. [editor V.S.Zemskov] Computer designing of inorganic compounds: use of databases and methods of artificial intelligence; Institute metallurgy and sience of material named for A.A.Bajkov.-of M.: Nauka.-2005.


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