The Properties Generality Principle and Knowledge Discovery Classification

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***Abstract*—The paper examines the actual problem of automatic detection of hidden interpretable patterns in intelligent systems. The conceptual basis of the process of learning from examples is determined by the methods of class description and separation. Three basic principles are known: enumeration of class members, generality of properties and clustering. We propose an original method for implementing the principle of generality of properties based on the search for combinations of features that provide class distinction. The effectiveness of the approach is confirmed by the results of numerical experiment.**

***Keywords*—intelligent systems, pattern recognition, learning from examples, data mining**

I. Introduction

The development and large-scale implementation of information technologies has led to the accumulation of huge amounts of data, which today are organized into databases and data warehouses [1], [2]. Currently, the development of new methods aimed at improving the efficiency of representation and automatic knowledge extraction based on the analysis of large amounts of data is an urgent problem in computer science [3], [4].

The experience of using the structured query language (SQL) has shown its very limited capabilities in terms of discovering hidden patterns existing within the data. OLAP technology (interactive analytical data processing) is focused on the preparation of aggregated information on the basis of large data sets structured according to the multidimensional principle. At best, the technology provides for the extraction of knowledge from the data, which should be attributed to the "shallow" level of occurrence. The most interesting in practical terms are the hidden patterns, the detection of which is the focus of Data Mining [5]–[7].

In computer science, the problem of pattern recognition is one of the fundamental problems [8]–[10]. Its successful solution largely determines the progress in the field of artificial intelligence. Pattern recognition is the attribution of initial data to a certain class based on the selection of essential distinguishing features that characterize this data [11]–[14].

If a class is characterized by some common properties inherent in all its members, the construction of a recognition system can be based on the principle of generality of properties. The basic assumption in this case is that patterns of the same class have common properties reflecting their similarity [15], [16].

The paper proposes an original method of implementing the principle of generality of properties. It is assumed that as a result of analyzing the training data set (TS) it is possible to identify such a combination of features that ensure the distinction of classes. That eventually make the procedure of building a classification algorithm quite trivial. The effectiveness of the method is confirmed by the results of numerical experiment.

II. On Pattern Recognition Principles and Classification Problem

The basis of the idea of building automatic recognition systems are the methods of describing and separating classes (Fig. 1) [17].

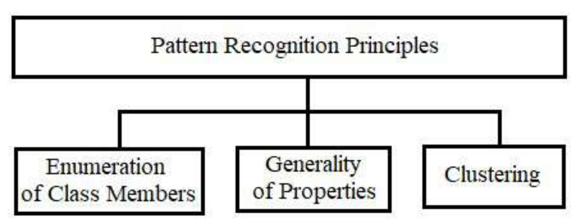

Figure 1. Principles of Pattern Recognition.

When a class is defined by an enumeration of its constituent objects, the construction of a pattern recognition system can be based on the principle of belonging to this enumeration. A set of objects of the class is memorized by the recognition system, and when a new object is presented to the system, it assigns it to the class to which the object located in the system's memory that matches the new one belonged (Fig. 2).

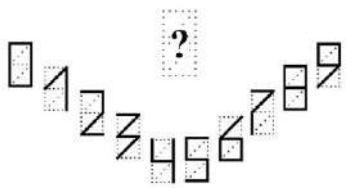

Figure 2. Enumeration of Class Members.

If all objects of one class have a number of common properties or features that are absent or have other values in all representatives of other classes, then the construction of the recognition system can be implemented on the basis of the principle of generality of properties (Fig. 3).

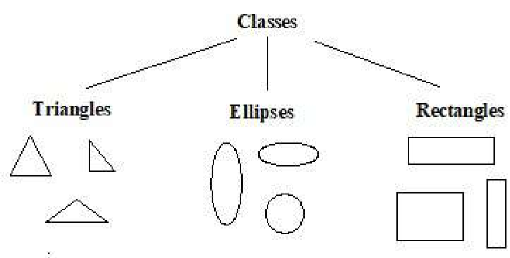

Figure 3. Generality of Properties.

When the objects of a class are vectors in the feature space, the class can be considered as a cluster. If clusters of different classes are separated far enough from each other, then the construction of the recognition system can be carried out using the clustering principle (Fig. 4).

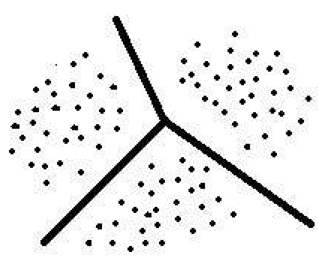

Figure 4. Clustering.

Traditionally, when building automatic pattern recognition systems, three main problems are solved. The first one is devoted to the issues of representation of the initial data obtained as a result of measurements of the recognized object. The second task is related to the extraction of essential features and properties from the initial data. The third one consists in finding optimal decision rules for classification [18], [19].

In [19], the author, discussing the problem of the simplicity of the learning process in pattern recognition, notes the existence of two different approaches to its implementation. In author's opinion, in the vast majority of studies (the first group), the learning process is aimed at constructing solving rules that ensure the extremum of a pre-selected criterion. In the second group, the focus is on understanding the principles of forming the description of recognition objects, within which the recognition process becomes extremely simple. Learning in this case is seen as a process of constructing a space that is universal, if not for all, then for a wide class of tasks. Unfortunately, in the author's opinion, this group of studies is very few and such an approach to solving the recognition problem is still poorly studied.

Today, pattern recognition is dominated by an approach in which training is reduced to solving an optimization problem. The training process begins with the selection of an initial model (a parametric family of algorithms), and then it is assumed that the "training + testing" scenario is repeatedly executed. In fact, training is an iterative process in which positive and negative reinforcements are used to form the desired patterns of classifier behavior.

In this case, it should be pointed out that there are at least two serious problems. First, model selection is a non-trivial task performed by a data science specialist, and therefore the training process can be implemented only in an automated mode. Second, the only result of training is a classification algorithm, which is an uninterpretable "black box".

It is proposed to consider an alternative approach, when the construction of the classification algorithm is performed not within the framework of the optimization problem, but on the basis of the analysis of the properties of the considered classes. As a result of such analysis, the distinguishing properties are determined by the mutual placement of the areas of class definition — patterns.

Before proceeding to the presentation of the alternative approach, let us consider the classical version of the mathematical formulation of the recognition problem.

In the paper by Y. I. Zhuravlev [20], the following formulation of the recognition problem (*classification or Z problem*) is given:

Let there be a set of admissible objects M. The set is covered by a finite number of subsets $K_1, \ldots, K_l : M = \bigcup_{i=1}^{l} K_i$, *called classes. The partitioning of the set M is not completely defined, only some information* I_o *about classes* $K_1, \ldots, K_l$ *is given. Similarly, an admissible object S is defined by the values of some characteristics. The set of given values defines the description I(S) of the object S.*

The main problem (problem Z) is to compute the values of predicates $P_j(S) - S \in K_j, j = 1, 2, \ldots, l$, *from the information* $I_o(K_1, \ldots, K_l)$ *and the description of the admissible object I(S).*

The information I_o is commonly called training information, and the predicates $P_j(S)$ are called elementary predicates.

In this formulation of the problem, it is actually required to construct some algorithm $A(I_0(K_1,\dots,K_l), I(S)) = (\alpha_1^A(S)\dots\alpha_l^A(S))$, where $\alpha_1^A(S) = P_j(S), j = 1,2,\dots,l$.

Obviously, the result of solving the problem Z is an algorithm with certain properties. In machine learning, the construction of such an algorithm is done within a scenario:

1) Some parametric family (model) of algorithms is selected;
2) The initial values of the parameters are fixed, and thus a specific algorithm is set;
3) The final setting of the algorithm to the subject domain is carried out during its training based on the training set data.

In this case, the learning process is reduced to the construction of algorithms (*decision rules*) that ensure the extremum of some criterion. Such a criterion, for example, can be the value of the average risk in a special class of decision rules. That is, at the beginning, the class of decision rules is defined up to parameters, and the training is reduced to finding the values of parameters that provide the extremum for the selected criterion.

Thus, in the most general form, the recognition problem can be written as follows: *The object description space is given, in which it is necessary to construct surfaces separating classes.*

In this formulation, the emphasis is on the construction of the algorithm *(on the construction of surfaces separating the classes)*, and therefore the problem has a pronounced algorithm-centric character.

In a more detailed analysis of the problem statement Z, we can propose an alternative variant of its formulation, when to find a solution the emphasis is shifted to the study of the property of classes. The new problem statement in this case is as follows.

Let two sets $I_0, I(S)$ be given, i. e., admissible training information $I_0(K_1,\dots,K_l)$ and descriptions $I(S)$ of admissible objects $S \in M$, respectively.

It is required, based on the analyses of the of information $I_0(K_1,\dots,K_l)$, to find the set of distinguishing qualities of classes $Q(K_1,\dots,K_l)$ such that $K_i \cap K_j = \emptyset, \forall i \neq j$ (where $i,j = 1,2,\dots,l$) and using then the set $Q(S)$ to compute the values of predicates $P_j(S), j = 1,2,\dots,l$.

In this formulation, the solution of the problem is emphasized on the study of the property of classes and identification of features that provide class distinction. The recognition problem in this formulation is proposed to be called the Knowledge Discovery Classification Problem (KDC problem).

III. Method for Solving the KDC Problem

Let *M* be a set of objects, called admissible objects, and let it be covered by a finite number of subsets $K_1,\dots,K_l : M = \bigcup_{i=1}^{l} K_i$ called classes. The partition *M* is not completely defined. Let an a priori dictionary of features $F = \{f_1,\dots,f_n\}$ be given and on its basis only partial information $X = \bigcup_{i=1}^{l} X_i$ about classes $K_1,\dots,K_l$ is given. Similarly, an admissible object *S* is defined on the basis of the features of the a priori dictionary.

The classification problem is to compute the values of predicates $P_j(S) - S \in K_j, j = 1,2,\dots,l$, based on the partial information X about classes $K_1,\dots,K_l$ and the description of the admissible object *S*.

In the framework of the classical approach, the mathematical formulation of the classification problem is as follows: *Let X be the set of object descriptions and Y be the set of admissible classification answers. There is an unknown target dependency y*: X → Y, the values $X^m = \{(x_1,y_1),\dots,(x_m,y_m)\}$ of which are known only for the objects of the training set. It is necessary to construct an algorithm a: X → Y, which would approximate this target dependency not only on the objects of the finite set, but also on the whole set X.*

To solve the problem, first the model of algorithms is specified up to parameters, and then training is carried out by finding such values of parameters that provide the extremum of the selected criterion. The experience of practical use of this scenario has revealed a number of problematic points.

The choice of a model of algorithms *A = a : X → Y* is actually a non-trivial task. In this case, it is not so much about science as about the art of algorithm construction [21], [22]. Moreover, learning can be realized only in an automated mode. And the final algorithm *a: X → Y* is a “black box”. It approximates an unknown target dependency, which cannot be interpreted in terms of the subject domain.

The above drawbacks are avoided by using an alternative approach, which is based on the idea of the compactness hypothesis that classes form compactly localized subsets in the object space [23]–[25].

The mathematical formulation of the *Knowledge Discovery Classification Problem* in this case is as follows: *Let X be the set of object descriptions and Y be the set of admissible answers for their classification. There is an unknown target dependency y* : X → Y, the values of which $X^m = \{(x_1,y_1),\dots,(x_m,y_m)\}$ are known only for the objects of the training set. It is required to find feature spaces in which classes do not intersect, and on their basis to construct an algorithm a : X → Y which would approximate this target dependency not only on the objects of the finite set, but also on the whole set X.*

The KDC problem is solved in two steps. First, the feature spaces in which the class patterns do not intersect are searched. After that, the construction of the classification algorithm becomes a simple procedure.

The initial data of the *Knowledge Discovery Classification Problem* are the alphabet of classes $K = \{K_1, \ldots, K_l\}$, a priori dictionary of features $F = \{f_1, \ldots, f_n\}$, training set $X_m = \{(x_1, k_1), \ldots (x_m, k_m)\}$, where k_i is the label of one of the classes of the alphabet K.

Let us denote by $V = \{v_1, \ldots, v_q\}$ the set of all possible combinations of features from F. In total V contains $q = \sum_{i=1}^{n} C_n^i = 2^n - 1$ different subsets.

At first glance, the solution to the KDC problem should involve performing a brute-force search on the set V. However, using the properties of combinations of features the search can be significantly reduced.

Let us demonstrate by concrete examples what properties of class distinction can be possessed by features and combinations of features of the dictionary F. Suppose that two classes of objects ***** and **+** are given, and for some pair of attributes f_i and f_j the distribution of objects of these classes is as follows (Fig. 5).

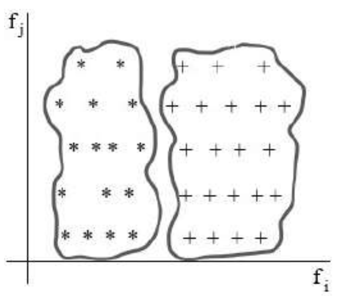

Figure 5. The first variant of mutual placement of objects.

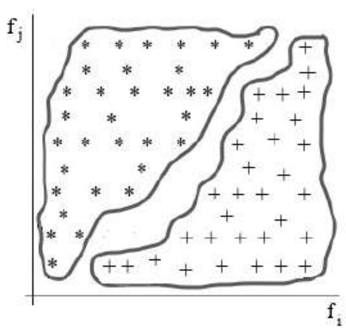

Figure 6. The second variant of mutual placement of objects.

Obviously, the feature f_i in Figure 5 has the property of distinguishing two classes, while the feature f_j has no such property. In addition, all combinations of features containing f_i, have the property of distinguishing two classes, i. e. the patterns of classes in the corresponding feature space do not intersect.

Figure 6 shows that each of the features f_i and f_j individually does not have the property of distinguishing between the two classes, while the combination of features f_i and f_j has such a property.

If each of the features of the original a priori dictionary has the property of class distinction, then the solution of the KDC problem is reduced from the brute-force search to the consideration of n variants.

The algorithm of searching for combinations of features on the set $V = \{v_1 \ldots, v_q\}$ that provide class distinction, as a result of the following steps:

Step 1. Select a subset $V^+ = \{v_1^+, \ldots, v_+^i\}$ of V, where v_i^+ contains only one feature.

Step 2. For each v_i^+ we construct class patterns (class definition areas) and compare their mutual placement [26].

Step 3. If class patterns do not intersect, then feature v_i^+ is included in the set $V^* = \{v_1^*, \ldots, v_k^*\}$.

Step 4. Exclude from the set $V = \{v_1, \ldots, v_q\}$ the subset $V^+ = \{v_1^+, \ldots, v_n^+\}$ and get $V^\Delta = \{v_1^\Delta, \ldots, v_p^\Delta\}$.

Step 5. Exclude from V^Δ all combinations of v_i^Δ, that contain any combination from $V^* = \{v_1^*, \ldots, v_k^*\}$.

Step 6. Take the next combination v_i^Δ from V^Δ and build a feature subspace based on it.

Step 7. In this feature subspace, we construct class patterns and compare their mutual placement.

Step 8. If the class patterns do not intersect, we include the combination of features v_i^Δ in the set V^*, and exclude from V^Δ all combinations that contain v_i^Δ.

Step 9. Repeat the process until V^Δ is empty.

The algorithm will result in the set $V^* = \{v_1^*, \ldots, v_t^*\}$, where $0 \leq t \leq q$. Based on the combinations $v_i^* \in V^*$, we formulate the previously hidden and empirically revealed regularities: «in the feature space of a subset v_i^* classes do not intersect».

Note that within the framework of solving a particular applied problem, all combinations of features v_i^* can be interpreted in terms of the subject domain.

Combinations of features $v_i^* \in V^*$ define decision spaces in which class patterns do not intersect. In such spaces, the compactness hypothesis condition is satisfied and classification is performed by the rule:

- for each combination of features $v_i^* \in V^*$ (where $i = 1, 2, \ldots, t$) and based on the training set data we build cluster structures $P_1^i, \ldots, P_l^i$ — patterns of classes $K_1, \ldots, K_l$ [26];
- investigated object $S \in K_m$ if $S \in P_m^i \forall i = 1, 2, \ldots, t$.

To exemplify the demonstration of the generality principle in Figure 3, the following variant of the classification algorithm construction can be proposed:

There is an alphabet of classes K={Triangles, Ellipses, Rectangles} and an a priori dictionary of features F={area of figure, perimeter of figure, number of angles}.

It is obvious that only the feature "number of angles" has the property of class distinction, because for all figures of class Triangles the value of the feature is equal to 3, for class Ellipses - equal to 0, for class Rectangles - equal to 4. Hence $V^* = \{number\ of\ angles\}$ and the classification algorithm is as follows:

IF (number of angles = 3) THEN Triangles
ELSE IF (number of angles = 0) THEN Ellipses
ELSE Rectangles

IV. Example of Solving the KDC Problem

Let's demonstrate the results of solving the KDC problem based on model data. Let's say we're given:

- classes **Not3** (there is no digit 3 in the number) and **Yes3** (there is at least one digit 3 in the number);
- a priori dictionary of features *F = {Units, Tens}*;
- training set, which consists of 250 two-digit integers, among which 200 have no digit 3 and 50 have at least one digit 3.

Table I shows the feature values of *Units* and *Tens* in the training set used in the numerical experiment.

Table I. Values of Units and Tens in the training set

Units / **Tens**	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
0	2	2	2	3	2	3	2	3	2	3
1	3	3	2	3	2	3	3	2	3	2
2	2	3	2	3	2	2	2	3	3	2
3	3	2	2	2	3	2	3	2	2	3
4	2	3	2	3	2	3	2	3	3	2
5	3	2	3	3	3	3	3	2	3	2
6	3	2	3	2	3	2	3	2	3	2
7	2	3	3	3	2	3	2	3	2	3
8	3	2	2	3	3	2	2	2	3	2
9	2	3	2	3	3	3	2	2	2	3

Table II summarizes the results of class pattern intersection study based on the features *Units*, *Tens*, where $Not3_i$ is the number of $Not3_i$ class representatives for the i-th digit; $Yes3_i$ is the number of $Yes3_i$ class representatives for the i-th digit.

Table II shows that neither the Units feature nor the Tens feature provides an absolute separation between the **Not3** and **Yes3** classes.

Table III summarizes the results of the study on the intersection of class patterns based on the combination of features *(Tens, Units)*.

Table III shows that:

- all numbers of class *Not3* have no digit 3, and all numbers of class *Yes3* have at least one digit 3;
- combination of features *(Tens, Units)* provides absolute separation of *Not3* and *Yes3* classes;

Table II. Results for features Units and Tens

	Units		**Tens**	
Digit	**Not3**	**Yes3**	**Not3**	**Yes3**
0	22	3	21	3
1	23	3	23	2
2	21	3	21	2
3	0	2	0	24
4	22	3	22	3
5	24	3	24	2
6	21	2	23	3
7	22	3	23	2
8	24	3	21	2
9	21	3	22	3

Table III. Results for the combination of features (Tens, Units)

T,U	N3	Y3	T,U	N3	Y3	T,U	N3	Y3	T,U	N3	Y3
0,0	2	0	2,5	2	0	5,0	3	0	7,5	3	0
0,1	2	0	2,6	2	0	5,1	2	0	7,6	2	0
0,2	2	0	2,7	3	0	5,2	3	0	7,7	3	0
0,3	0	3	2,8	3	0	5,3	0	3	7,8	2	0
0,4	2	0	2,9	2	0	5,4	3	0	7,9	3	0
0,5	3	0	3,0	0	3	5,5	3	0	8,0	3	0
0,6	2	0	3,1	0	2	5,6	3	0	8,1	2	0
0,7	3	0	3,2	0	2	5,7	2	2	8,2	2	0
0,8	2	0	3,3	0	2	5,8	3	0	8,3	0	3
0,9	3	0	3,4	0	3	5,9	2	0	8,4	3	0
1,0	3	0	3,5	0	2	6,0	3	0	8,5	2	0
1,1	3	0	3,6	0	3	6,1	2	0	8,6	2	0
1,2	2	0	3,7	0	2	6,2	3	0	8,7	2	0
1,3	0	3	3,8	0	2	6,3	0	2	8,8	3	0
1,4	2	0	3,9	0	3	6,4	3	0	8,9	2	0
1,5	3	0	4,0	2	0	6,5	2	0	9,0	2	0
1,6	3	0	4,1	3	0	6,6	3	0	9,1	3	0
1,7	2	0	4,2	2	0	6,7	2	0	9,2	2	0
1,8	3	0	4,3	0	3	6,8	3	0	9,3	0	3
1,9	2	0	4,4	2	0	6,9	2	0	9,4	3	0
2,0	2	0	4,5	3	0	7,0	2	0	9,5	3	0
2,1	3	0	4,6	2	0	7,1	3	0	9,6	2	0
2,2	2	0	4,7	3	0	7,2	3	0	9,7	2	0
2,3	0	3	4,8	3	0	7,3	0	3	9,8	2	0
2,4	2	0	4,9	2	0	7,4	2	0	9,9	3	0

- the definition areas of *Not3* and *Yes3* classes do not intersect and are presented below (Fig. 7).

The classification algorithm is built on the basis of a rule: *IF (Units = 3 or Tens = 3) THEN Yes3 ELSE Not3.*

So, as a result of solving the KDC problem in automatic mode, the training data set were analyzed. The initially hidden regularity *«the combination of features (Tens, Units) provides the distinction between classes Not3 and Yes3 by the rule IF (Units = 3 or Tens = 3) THEN Yes3 ELSE Not3»* was found, and the classification algorithm was built on its basis.

V. Conclusion

The paper presents an original approach for solving the problem of learning from examples which is based on the use of the properies generality principle. The method of the principle implementation is proposed which provides

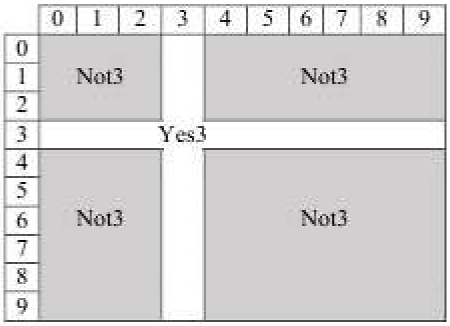

Figure 7. Definition areas of Not3 and Yes3 classes.

for automatic detection of hidden interpretable patterns in the training data set. The revealed patterns can be used then to construct a classification algorithm.

The learning algorithm for identifying combinations of features that have the property of class distinction is described. As a result of analyzing the training data set, the informativeness estimates of combinations of distinguishing features (from the point of view of classes) are automatically calculated and a classifier is built.

Based on model data, the results of applying the developed method to solve the classification problem are presented.

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ПРИНЦИП ОБЩНОСТИ СВОЙСТВ И KD-КЛАССИФИКАЦИЯ

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В работе исследуется актуальная проблема автоматического обнаружения скрытых интерпретируемых закономерностей в интеллектуальных системах. Концептуальную основу процесса обучения по прецедентам определяют способы описания и разделения классов. Известны три базовых принципа: перечисления членов класса, общности свойств и кластеризации. Предлагается оригинальный метод реализации принципа общности свойств, основанный на поиске сочетаний признаков, обеспечивающих различение классов. Эффективность подхода подтверждается результатами численного эксперимента.

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