Fuzzy Decision Tree Based Classification of Psychometric Data

Vitaly Levashenko*, Elena Zaitseva*, Krzysztof Pancerz[†] [‡] and Jerzy Gomuła[§] [¶]

*University of Zilina, Slovakia

Email: Vitaly.Levashenko@fri.uniza.sk, elena.zaitseva@fri.uniza.sk

[†]University of Management and Administration in Zamość, Poland

Email: kpancerz@wszia.edu.pl

[‡]University of Information Technology and Management in Rzeszów, Poland

[§]The Andropause Institute, Medan Foundation, Warsaw, Poland

Email: jerzy.gomula@wp.pl

[¶]Cardinal Stefan Wyszyński University in Warsaw, Poland

Abstract—**For five years, the Copernicus system - a tool for computer-aided diagnosis of mental disorders based on data coming from psychometric tests - has been developed. This tool uses a variety of classification ways for differential interprofile diagnosis. In the current version of the tool, psychometric data come from the Minnesota Multiphasic Personality Inventory (MMPI) test. In this paper, we describe another machine learning approach, based on fuzzy decision trees, for classification of psychometric data. The algorithm for generation of fuzzy decision trees used by us is based on cumulative information estimations of initial data. Due to the promising results of classification of MMPI data, the presented approach will be implemented in the Copernicus system.**

I. INTRODUCTION

SO FAR, there have not been developed universal machine learning and data mining methods which could be applied for each kind of data, delivering expected results. Each kind of data requires an individual approach to them, and what follows, designing suitable, specialized methods for them. Classification models can be obtained in various ways (cf. [1], [2], [3]). Each way leads to obtaining a set of rules characterized by different coefficients describing their classification ability/quality. One of the main tasks of building decision support systems for computer-aided diagnosis of patients is to search for efficient methods of classification of new cases unseen earlier. Our research concerns psychometric data coming from the Minnesota Multiphasic Personality Inventory (MMPI) test [4]. MMPI is used to count the personality-psychometric dimensions which help in diagnosis of mental diseases. A brief information about this test is included in Section II.

In years 1998-1999, a team of researchers consisting of W. Duch, T. Kucharski, J. Gomuła, R. Adamczak created two independent rule systems devised for the nosological diagnosis of persons that may be screened with the MMPI-WISKAD test [5]. In the literature, we can also find descriptions of some other computer tools for classification of MMPI profiles, e.g., based on the Fortran program [6], "Panda" [7]. However, these tools are now mature. For five years, our research has been focused on creating a new computer tool called

the Copernicus system. We started creation of the system in 2009. The main goal of this tool is to support clinical psychologists in differential and clinical diagnosis based on the overall analysis of profiles of patients examined by means of personality inventories. The tool has been designed for the Java platform. We can distinguish three main parts of the Copernicus system:

- Knowledge base.
- Multiway classification engine.
- Visualization engine.

The development of the Copernicus system (consecutive versions) over five years has been described in [8], [9], [10].

In the paper, we describe another machine learning approach that we plan to implement in the Copernicus system. This approach uses fuzzy decision trees proposed in [11]. That approach, based on cumulative information estimations of initial data, is brought back in Section III. Results of experiments made on over 1700 cases showed that the approach looks very promising.

II. MMPI DATA

The Minnesota Multiphasic Personality Inventory (MMPI) test [4] delivers psychometric data on patients with selected mental disorders. Originally, the MMPI test was developed and published in 1943 by a psychologist S.R. McKinley and a neuropsychiatrist J.Ch. Hathaway from the University of Minnesota. Later, the inventory was adapted in above fifty countries. The MMPI-WISKAD personality inventory is the Polish adaptation of the American inventory. It has been used, among other modern tools, for carrying out nosological differential diagnosis in psychiatric wards. MMPI is also commonly used in scientific research. The test is based upon the empirical approach and originally was translated by M. Chojnowski (as WIO) [12] and elaborated by Z. Płużek (as WISKAD) in 1950 [13]. American norms were accepted there. Based upon received responses (*"Yes"*, *"Cannot Say"*, *"No"*) to selected questions we may make up a diagnosis for the subject being examined.

After examination by means of the MMPI test, each case (patient) x is described by a data vector $A(x)$ consisting of thirteen descriptive attributes: $A(x) = [A_1(x), A_2(x), ..., A_{13}(x)]$. A data vector is the so-called MMPI profile. The profile always has a fixed and invariable order of its constituents (attributes). If we have training data, then to each case x we also add one decision attribute Cl - a class (*nosological type* or *reference class*) to which a patient is classified. For the training data (which are used to learn or extract relationships between data), we have a tabular form (see example in Table I) which is formally called a decision system (decision table) $S = (Obj, Attr, Cl)$ in the Pawlak's form [14]. Obj is a set of cases (patients), $Attr$ is a set of descriptive attributes corresponding to scales, and Cl is a decision attribute determining a decision class.

The MMPI profile (data vector) can be divided into two parts. The validity part of the profile consists of three scales: L (laying) - attribute A_1, F (atypical and deviational answers) - attribute A_2, K (self-defensive mechanisms) - attribute A_3. The clinical part of the profile consists of ten scales: $1.Hp$ (Hypochondriasis) - attribute A_4, $2.D$ (Depression)- attribute A_5 , $3.Hy$ (Hysteria) - attribute A_6, $4.Ps$ (Psychopathic Deviate) - attribute A_7, $5.Mf$ (Masculinity/Femininity) - attribute A_8, $6.Pa$ (Paranoia) - attribute A_9, $7.Pt$ (Psychasthenia) - attribute A_{10}, $8.Sc$ (Schizophrenia) - attribute A_{11}, $9.Ma$ (Hypomania) - attribute A_{12}, $0.It$ (Social introversion) - attribute A_{13}. The clinical scales have numbers attributed to them so that a profile can be encoded to avoid negative connotations connected with the names of scales. Values of attributes are expressed by the so-called T-scores. The T-scores scale, which is traditionally attributed to MMPI, represents the following parameters: offset ranging from 0 to 100 T-scores, average equal to 50 T-scores, standard deviation equal to 10 T-scores.

In our experiments, we have used a data set, collected by T. Kucharski and J. Gomuła from the Psychological Outpatient Clinic, consisting of over 1700 patients (women) classified by a clinic psychologist. The data for the analysis (i.e., profiles of patients) were selected using the competent judge method (the majority of two-thirds of votes of three experts). Each case is assigned to one of nineteen nosological classes and the reference class (*norm*). Each class corresponds to one of psychiatric nosological types: neurosis (*neur*), psychopathy (*psych*), organic (*org*), schizophrenia (*schiz*), delusion syndrome (*del.s*), reactive psychosis (*re.psy*), paranoia (*paran*), sub-manic state (*man.st*), criminality (*crim*), alcoholism (*alcoh*), drug addiction (*drug*), simulation (*simu*), dissimulation (*dissimu*), and six deviational answering styles (*dev1*, *dev2*, *dev3*, *dev4*, *dev5*, *dev6*).

III. FUZZY DECISION TREES

A new greedy version of the Fuzzy ID3 algorithm based on cumulative information estimations of initial data has been proposed in [11]. It can be used to generate understandable fuzzy classification rules. Cumulative information estimations have been introduced in [15]. In this section we briefly recall basics of the Fuzzy ID3 algorithm.

Let us assume, that data describing cases are collected in the form of a decision system (decision table) $S = (Obj, Attr, Cl)$ (cf. Section II). In the recalled approach, for each real valued attribute $A_i \in Attr$ describing cases, fuzzy partitions A_{i_1}, A_{i_2}, ..., $A_{i_{k_i}}$, with ranges $[0, 1]$, are determined (see an example in Figure 1). The fuzzification of attribute values $A_i(u)$ for a given case $u \in Obj$ is performed by analysing the corresponding values of membership functions, i.e., $\mu_{A_{i1}}(u)$, $\mu_{A_{i2}}(u)$, ..., $\mu_{A_{ik}}(u)$. Analogously, the decision attribute Cl can be fuzzified, i.e., we obtain Cl_1, Cl_2, ..., Cl_m. In case of symbolic decision attribute values, a number of partitions is equal to the number of possible values of this attribute and membership functions take values either 0 or 1. Each attribute value can be seen as a likelihood estimate. In the approach, a particular case is assumed when the sum of membership function values of all partitions equals to 1. To transform numeric attribute values to triangular fuzzy data, the algorithm presented in [16] is used.
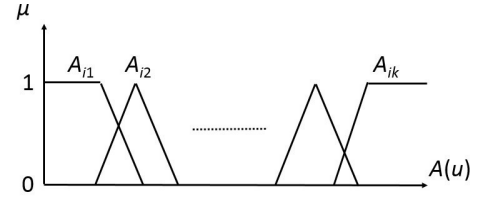

Fig. 1. An example of fuzzy partitions.

The cardinality measure $M(A_{i_1})$ for each A_{i_1} is calculated as:

$$M(A_{i_1}) = \sum_{u \in Obj} \mu_{A_{i1}}(u).$$

The cumulative joint information JI for Cl_j is:

$$JI(Cl_j) = \log_2 N - \log_2 M(Cl_j),$$

where N is a number of cases, i.e., the cardinality of Obj.

The cumulative joint information JI for Cl_j and $\mathbf{A}_q$ is:

$$JI(Cl_j, \mathbf{A}_q) = \log_2 N - \log_2 M(Cl_j \times A_{i_1} \times \cdots \times A_{q_{k_q}})$$

The cumulative conditional entropy H between Cl and A_{i_q} with a given $\mathbf{A}_q$ is:

$$H(B|\mathbf{A}_q, A_{i_q}) = \sum_{j=1}^{m} M(B_j \times \mathbf{A}_q) \times [JI(B_j, \mathbf{A}_q) - JI(\mathbf{A}_q)]$$

The cumulative conditional entropy H between Cl and A_i with a given $\mathbf{A}_q$ is:

$$H(B|\mathbf{A}_q, A_i) = \sum_{j=1}^{k_i} H(B|\mathbf{A}_q, A_{i_{k_i}}).$$

The cumulative mutual information I for A_i with a given $\mathbf{A}_q$ is:

$$I(B|\mathbf{A}_q, A_i) = H(B|\mathbf{A}_q) - H(B|\mathbf{A}_q, A_i).$$

These information estimations are used for forming new criteria of fuzzy decision tree induction (see [11]).

TABLE I
THE TRAINING DATA (FRAGMENT)

Attribute	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}	A_{12}	A_{13}	Cl
Scale	L	F	K	$1.Hp$	$2.D$	$3.Hy$	$4.Ps$	$5.Mf$	$6.Pa$	$7.Pt$	$8.Sc$	$9.Ma$	$0.It$	
#1	55	65	50	52	65	57	63	56	61	61	60	51	59	$norm$
#2	50	73	53	56	73	63	53	61	53	60	69	45	61	org
#3	56	78	55	60	59	54	67	52	77	56	60	68	63	$paran$
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...

TABLE II
EXEMPLARY FUZZIFICATION OF DESCRIPTIVE ATTRIBUTE VALUES (FOR
CASE #1)

Attribute A_i	A_{i_1}	A_{i_2}	A_{i_3}	A_{i_4}
A_1	0.077734	0.922266	0.000000	0.000000
A_2	0.298226	0.701774	0.000000	0.000000
A_3	0.000000	0.771691	0.228309	0.000000
A_4	1.000000	0.000000	0.000000	0.000000
A_5	0.453095	0.546905	0.000000	0.000000
A_6	0.858034	0.141966	0.000000	0.000000
A_7	0.238494	0.761506	0.000000	0.000000
A_8	0.119084	0.880916	0.000000	0.000000
A_9	0.725949	0.274051	0.000000	0.000000
A_{10}	0.579492	0.420508	0.000000	0.000000
A_{11}	0.873296	0.126704	0.000000	0.000000
A_{12}	0.781460	0.218540	0.000000	0.000000
A_{13}	0.000000	0.782395	0.217605	0.000000

There are two tuning parameters α and β used in the algorithm. Expanding a tree branch is stopped when either the frequency f of the branch is below α or when more than β per cent of cases left in the branch have the same decision class label.

IV. EXPERIMENTS

Experiments have been performed on a data set described in Section II. Each descriptive attribute has been fuzzified using four partitions (see an example in Table II). An exemplary fuzzy decision tree is shown in Figure 2. A decision attribute Cl has been fuzzified using 20 partitions because it has symbolic character (see an example in Table III). Cases are classified into 20 decision classes.

We have calculated fuzzy decision trees for several parameters α and β. The results (classification ability) of experiments are collected in Table IV. The best classification result has been obtained for $\alpha = 0.001$ and $\beta = 0.999$. We can compare classification ability of the presented approach with other classic machine learning approaches (see Table V).

We also refer the readers to our earlier papers where results of classification of MMPI profiles using a variety of approaches are presented. In [17], we have described the tests of several algorithms included in the following software tools:

- The Rough Set Exploration System (RSES) - a software tool featuring a library of methods and a graphical user interface supporting a variety of rough set based computations [18].
- NGTS - a system developed to generate decision rules using the algorithm called GTS (General-To-Specific) [19].

TABLE IV
RESULTS OF EXPERIMENTS FOR DIFFERENT PARAMETERS α AND β

α	β	Average classification error	Standard deviation
0.001	0.999	0.0823	0.0121
0.001	0.989	0.0823	0.0121
0.001	0.979	0.0829	0.0122
0.001	0.969	0.0838	0.0123
0.001	0.959	0.0846	0.0123
0.001	0.949	0.0854	0.0124
0.001	0.939	0.0865	0.0125
0.001	0.929	0.0878	0.0128
0.001	0.919	0.0896	0.0130
0.001	0.909	0.0915	0.0135
0.001	0.899	0.0937	0.0137
0.001	0.889	0.0959	0.0138
0.001	0.879	0.0978	0.0141
0.001	0.869	0.1001	0.0146
0.001	0.859	0.1030	0.0149
0.011	0.999	0.1646	0.1288
0.011	0.989	0.1648	0.1288
0.011	0.979	0.1650	0.1288
0.011	0.969	0.1653	0.1288
0.011	0.959	0.1656	0.1288
0.011	0.949	0.1660	0.1288
0.011	0.939	0.1667	0.1289
0.011	0.929	0.1675	0.1289
0.011	0.919	0.1684	0.1289
0.011	0.909	0.1693	0.1289
0.011	0.899	0.1703	0.1289
0.011	0.889	0.1715	0.1289
0.011	0.879	0.1727	0.1290
0.011	0.869	0.1745	0.1290
0.011	0.859	0.1766	0.1291
0.021	0.999	0.2100	0.1816
0.021	0.989	0.2102	0.1816
0.021	0.979	0.2102	0.1816
0.021	0.969	0.2103	0.1816
0.021	0.959	0.2104	0.1816
0.021	0.949	0.2110	0.1817

TABLE V
COMPARISON OF CLASSIFICATION ABILITIES OF DIFFERENT APPROACHES

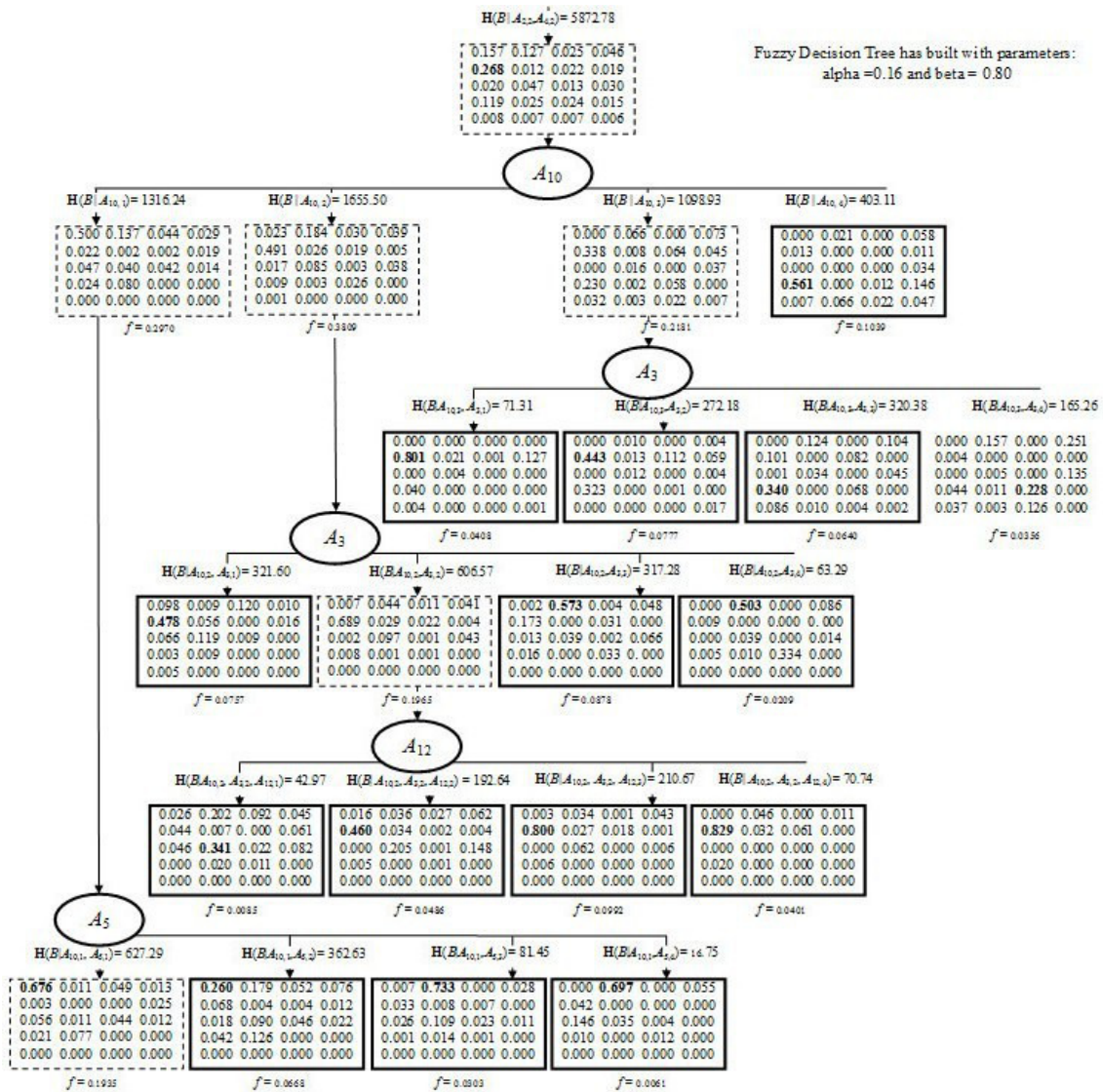| Method	Average classification error	Standard deviation
FDT	**0.0823**	**0.0121**
C4.5	0.0952	0.0149
CART	0.1407	0.1287
Bayes	0.1531	0.1288
k-NN	0.0937	0.0129

Fig. 2. An exemplary fuzzy decision tree.

- TreeSEEKER - a system containing several algorithms to generate decision trees [20].
- RuleSEEKER - a tool for generation and optimization of rule sets [21].

The main goal of experiments described in [22] was generation of efficient classification (decision) rules via decision trees on the basis of profiles of patients and selected indexes (e.g. Eichmann's indexes, Goldberg's indexes, Leary's indexes), calculated for profiles. Indexes added to profiles (scales) have been calculated using the Copernicus system. Next, for decision tree generation, the well-known C4.5 algorithm [23] (implemented in WEKA) has been used. Experiments with basic profiles (validity and clinical scales) and the extended ones (by adding different specialized indexes defined in the professional domain literature) have also been described in [24]. In [25], we have shown that it is possible to improve

classification accuracy of MMPI profiles by reduction or extension of the number of attributes with relation to the original data table. In [26], a problem of hybridization and optimization of the knowledge base for the Copernicus system has been presented. Another tests of classification algorithms, based on decision trees available in the WEKA system [3], have been described in [27]. The review of the variety of approaches (not only machine learning) implemented so far in the Copernicus system is shown in [10].

V. CONCLUSIONS AND FURTHER WORK

In the paper, we have presented another machine learning approach, based on fuzzy decision trees, for classification of psychometric data that is planned to be implemented in the Copernicus system - a tool for computer-aided diagnosis of mental disorders based on data coming from psychometric

TABLE III
EXEMPLARY FUZZIFICATION OF DECISION ATTRIBUTE VALUES (FOR CASE #1)

Cl_1	Cl_2	Cl_3	Cl_4	Cl_5	Cl_6	Cl_7	Cl_8	Cl_9	Cl_{10}	Cl_{11}	Cl_{12}	Cl_{13}	Cl_{14}	Cl_{15}	Cl_{16}	Cl_{17}	Cl_{18}	Cl_{19}	Cl_{20}
1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

tests. The presented approach is based on cumulative information estimations of initial data. Results of experiments against a background of our previous research looks very promising. The main goal of further work is to develop the interpretation of fuzzified attribute values and obtained decision rules from the point of view of diagnosticians. Moreover, there is a need to optimize the transformation method of attribute values from numeric to fuzzy set partition variables. The current version seems to be not optimal.

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