New Developments in Fuzzy Sets, Intuitionistic Fuzzy Sets, Generalized Nets and Related Topics. Volume II: Applications

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ISBN 83-894-7541-3

Dedicated to Professor Beloslav Riečan on his 75th anniversary

Intuitionistic fuzzy classifier – a tool for recognizing imbalanced classes

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Abstract

This paper is a continuation of our previous works on classification of imbalance and overlapping classes using intuitionistic fuzzy sets. We compare the results of recognizing imbalanced classes obtained via a fuzzy classifier and intuitionistic fuzzy classifier. Benchmark data sets are examined.

Keywords: Intuitionistic fuzzy sets, intuitionistic fuzzy classifier, imbalanced classes.

1 Introduction

Recognizing the imbalanced classes is a tough task for a classifier. Imbalanced class does need to be a small class – it may be a class with lots of elements but still far less that the other class. Usually, a two-category problem (Duda [14]) $positive/negative$ called also $legal/illegal$ classification problem with a relatively small class is considered. Constructing a classifier for such classes is both a theoretical challenge and a problem often met in different types of real tasks. Examples are given by Kubat at al. [18], Fawcett and Provost [15], Japkowicz [17],

New Developments in Fuzzy Sets, Intuitionistic Fuzzy Sets, Generalized Nets and Related Topics. Volume II: Applications *(K.T. Atanassow, W. Homenda, O. Hryniewicz, J. Kacprzyk, M. Krawczak, Z. Nahorski, E. Szmidt, S. Zadrożny, Eds.), IBS PAN - SRI PAS, Warsaw, 2012.*

Lewis and Catlett [19], Mladenic and Grobelnik [20], He and Garcia [16]. To solve the imbalance problems usually up-sampling and down-sampling are used but both methods interfere in the structure of the data, and in a case of overlapping classes even the artificially obtained balance does not solve the problem (some data points may appear as valid examples in both classes).

This paper is a continuation of our previous works (cf. Szmidt and Kukier [33], [34], [35]) on intuitionistic fuzzy approach to the problem of classification of imbalanced and overlapping classes. We consider a two–class classification problem ($legal$ – relatively small class, and $illegal$ – a bigger class).

The classifier using intuitionistic fuzzy sets has its roots in the fuzzy set approach proposed by Baldwin at al. [9]. In that approach the classes are represented by fuzzy sets generated from the relative frequency distributions representing the data points used as examples of the classes [9]. In the process of generating fuzzy sets a mass assignment based approach is adopted (Baldwin at al. [6], [9]). For the obtained model (fuzzy sets describing the classes), using a chosen classification rule, a testing phase is performed to assess the performance of the proposed method.

The intuitionistic fuzzy classifier we consider is similar to the above one in the sense of the same steps we perform. The main difference lies in making use of intuitionistic fuzzy sets for the representation of classes, and in exploiting the structure of intuitionistic fuzzy sets to obtain a classifier which better recognizes the relatively small classes.

Representation of the classes by intuitionistic fuzzy sets (first, training phase) is the crucial point of the method. The intuitionistic fuzzy sets are generated from the relative frequency distributions representing the data considered – according to the procedure given by Szmidt and Baldwin [23]. Having in mind recognition of the smaller class as good as possible we use the information about the hesitation margins making it possible to improve the results of data classification in the (second) testing phase. The obtained results in the testing phase were examined using confusion matrices making possible to explore detailed behavior of the classifiers (not only in the sense of general error/accuracy). We use simple cross validation method (with 10 experiments). Obtained results are compared with a fuzzy classifier. Two benchmark data sets are used - “Glass”, and “Wine” (cf. [40]).

2 Brief introduction to A-IFSs

One of the possible generalizations of a fuzzy set in X (Zadeh [38]) given by

$$A^{'} = \{< x, \mu_{A'}(x) > | x \in X\} \quad (1)$$

where $\mu_{A'}(x) \in [0, 1]$ is the membership function of the fuzzy set A', is an A-IFS (Atanassov [1], [3]) A is given by

$$A = \{< x, \mu_A(x), \nu_A(x) > | x \in X\} \tag{2}$$

where: $\mu_A : X \to [0, 1]$ and $\nu_A : X \to [0, 1]$ such that

$$0 \leq \mu_A(x) + \nu_A(x) \leq 1 \tag{3}$$

and $\mu_A(x)$, $\nu_A(x) \in [0, 1]$ denote a degree of membership and a degree of non-membership of $x \in A$, respectively. (Two approaches to the assigning memberships and non-memberships for A-IFSs are proposed by Szmidt and Baldwin [24]).

Obviously, each fuzzy set may be represented by the following A-IFS

$$A = \{< x, \mu_{A'}(x), 1 - \mu_{A'}(x) > | x \in X\} \tag{4}$$

An additional concept for each A-IFS in X, that is not only an obvious result of (2) and (3) but which is also relevant for applications, we will call (Atanassov [3])

$$\pi_A(x) = 1 - \mu_A(x) - \nu_A(x) \tag{5}$$

a *hesitation margin* of $x \in A$ which expresses a lack of knowledge of whether x belongs to A or not (cf. Atanassov [3]). It is obvious that $0 \leq \pi_A(x) \leq 1$, for each $x \in X$.

The hesitation margin turns out to be important while considering the distances (Szmidt and Kacprzyk [25], [26], [30], entropy (Szmidt and Kacprzyk [27], [31]), similarity (Szmidt and Kacprzyk [32]) for the A-IFSs, etc. i.e., the measures that play a crucial role in virtually all information processing tasks.

Hesitation margins turn out to be relevant for applications - in image processing (cf. Bustince et al. [11], [10]) and classification of imbalanced and overlapping classes (cf. Szmidt and Kukier [33], [34], [35]), group decision making, negotiations, voting and other situations (cf. Szmidt and Kacprzyk papers).

In our further considerations we will use operator $D_\alpha(A)$ (where $\alpha \in [0, 1]$) (Atanassov [3])

$$D_\alpha(A) = \{\langle x,\ \mu_A(x) + \alpha\pi_A(x),\ \nu_A(x) + (1 - \alpha)\pi_A(x)\rangle \,|\, x \in X\} \tag{6}$$

3 Intuitionistic fuzzy classifier

Details concerning construction of an intuitionistic fuzzy classifier are presented in Szmidt and Kukier [33], [34], [35]. Here we only remind the basic steps. First,

Table 1: The Confusion Matrix

	Tested Legal	Tested Illegal
Actual Legal	a	b
Actual Illegal	c	d

it is necessary to convert training data expressed as relative frequency distributions into intuitionistic fuzzy sets (cf. Szmidt and Baldwin [21], [22], [23]) describing *legal* and *illegal* classes in the space of all the attributes. The problem of granulation (symmetric or asymmetric model, number of intervals for the attributes) is described in details in Szmidt and Kukier [33], [34], [35]) In effect each data instance is described as an intuitionistic fuzzy element (all three terms are taken into account: membership value μ, non-membership value ν, and hesitation margin π). Taking into account that the hesitation margins assign (the width of the) intervals where the unknown values of memberships lie, we use operator $D_\alpha(A)$ (6) so that the elements of the class we are interested in, could be seen as good as possible (details in Szmidt and Kukier [33], [34], [35]). For our purposes, i.e., to "see" better the smaller class, the values of α (6) are from interval $[0.5, 1]$. For $\alpha = 0.5$ we obtain a fuzzy classifier. It is worth stressing that the case $\alpha = 1$ does not produce the best results. We built such models for each attribute separately, and next, aggregate the results (see Szmidt and Kukier [33], [34], [35]).

3.1 The Models of a Classifier Error

Traditionally *accuracy* of a classifier is measured as the percentage of instances that are correctly classified, and *error* is measured as the percentage of incorrectly classified instances (unseen data). But when the considered classes are imbalanced or when misclassification costs are not equal both the accuracy and the error are not sufficient.

Confusion Matrix

The confusion matrix (Table 1) is often used to assess a two–class classifier . The meaning of the symbols is
a – the number of correctly classified legal points,
b – the number of incorrectly classified legal points,
c – the number of incorrectly classified illegal points,
d – the number of correctly classified illegal points,

In result, the most often used measures to assess a classifier are:

$$Acc = \frac{legalls\ \ and\ \ illegals\ \ correctly\ \ classified}{total} = \frac{a+d}{a+b+c+d} \tag{7}$$

$$TPR = \frac{legalls\ \ correctly\ \ classified}{total\ \ legalls} = \frac{a}{a+b} \tag{8}$$

$$FPR = \frac{illegals\ \ incorrectly\ \ classified}{total\ \ illegals} = \frac{c}{c+d} \tag{9}$$

3.2 Results obtained

We present here the results obtained from an intuitionistic fuzzy classifier recognizing elements from two benchmark data sets - "Glass", and "Wine" (cf. [40]). To verify the classifier we use simple cross validation method (with 10 experiments). The examined data set was separated in each iteration into a training set and test set (50/50) by selecting examples randomly. For each experiment the mean of the accuracy measures, and their standard deviation were calculated. Results obtained by an intuitionistic fuzzy classifier are compared with the results obtained by a fuzzy classifier.

In Tables 2–3 there are results for "Glass" Identification database (cf. [40]) with 214 instances, 7 classes (4th class is empty), 10 attributes.

In Table 2 asymmetric granulation was applied, and $\alpha = 0.7$. Accuracy (7) for fuzzy classifier (*Acc FS*) is better than for intuitionistic fuzzy classifier (*Acc IFS*) for classes 1–3, is the same for both classifiers for class 5, and is better for intuitionistic fuzzy classifier for classes 6–7. But in all cases *TPR IFS* is better than *TPR FS* which means that intuitionisticc fuzzy classifier "sees" better the class we are interested in. Improving of *TPR* for intuitionistic fuzzy classifier is at cost of bigger values of *FPR* for classes 1–3. But it is worth stressing that for classes 5–7 we obtain both better accuracy and *TPR* for intuitionistic classifier whereas *FPR* is practically the same.

In Table 3 there are results for the same database "Glass", with the same parameter $\alpha = 0.7$ but with symmetric granulation. The *accuracy* of intuitionistic fuzzy classifier *Acc IFS* is lower than *accuracy* of fuzzy classifier *Acc FS* for each class. On the other hand, the values of *TPR IFS* are considerably better than the counterpart values of *TPR FS*. Unfortunately, better values of *TPR IFS*, i.e., better recognition of relatively smaller class by intuitionistic fuzzy classifier, accompany considerably bigger values of of *FPR IFS*. In other words, intuitionistic fuzzy classifier with symmetric granulation better recognizes relatively small classes but general accuracy, and recognition of other classes is worse.

Table 2: Results for Glass, $\alpha = 0.7$, asymmetric granulation

no class		Acc FS	Acc IFS	TPR FS	TPR IFS	FPR FS	FPR IFS
1	average	79.4	76.3	0.56	0.9	0.09	0.31
	standard deviation	3.3	3.3	0.12	0.04	0.05	0.05
2	average	74.8	60.9	0.48	0.85	0.48	0.85
	standard deviation	3.6	4.2	0.11	0.09	0.11	0.09
3	average	90.8	84.9	0	0.21	0.01	0.09
	standard deviation	1.0	3.7	0	0.14	0.01	0.04
5	average	93.3	93.3	0.09	0.17	0.01	0.01
	standard deviation	1.0	1.2	0.09	0.12	0.01	0.01
6	average	95.6	97.0	0.12	0.42	0	0
	standard deviation	1.2	1.1	0.18	0.23	0	0
7	average	92.7	94.7	0.44	0.68	0.01	0.02
	standard deviation	1.4	1.7	0.14	0.17	0.01	0.01

Table 3: Results for Glass, $\alpha = 0.7$, symmetric granulation

no class		Acc FS	Acc IFS	TPR FS	TPR IFS	FPR FS	FPR IFS
1	average	71.5	60.3	0.25	0.94	0.05	0.57
	standard deviation	2.8	3.2	0.13	0.06	0.04	0.05
2	average	73.0	54.0	0.46	0.91	0.11	0.67
	standard deviation	2.6	3.2	0.14	0.07	0.07	0.07
3	average	89.4	44.4	0.06	0.84	0.03	0.59
	standard deviation	2.6	4.1	0.09	0.12	0.04	0.05
5	average	94.0	92.4	0.56	0.74	0.03	0.06
	standard deviation	2.2	3.3	0.2	0.15	0.02	0.04
6	average	96.2	94.3	0.48	0.64	0.01	0.04
	standard deviation	1.5	2.6	0.22	0.22	0.01	0.03
7	average	94.7	92.5	0.8	0.86	0.03	0.07
	standard deviation	1.9	1.5	0.12	0.1	0.02	0.02

In Tables 4–5 there are results for "Wine" database (cf. [40]) – 178 instances, 3 classes, 13 attributes (all continuous).

In Table 4 results for asymmetric granulation, and $\alpha = 0.7$ are presented. General accuracy of intuitionistic fuzzy classifier *Acc IFS* is better or equal to accuracy obtained by a fuzzy classifier *Acc FS*. More, *TPR IFS* is always better than *TPR FS* (0.99 instead of 0.92 for class 1, 0.97 instead 0.86 for class 2, 0.97 instead of 0.91 for class 3), which means that intuitionistic fuzzy classifier sees always better relatively smaller class than fuzzy classifier. Standard deviation (*TPR*) is lower for intuitionistic fuzzy classifier. *FPR IFS* is worse than *FPR FS* but the changes are not big (0.02 instead of 0.01 for class 1, 0.08 instead of 0 for class 2, and 0.01 instead of 0 for class 3.

In Table 5 results for symmetric granulation, and $\alpha = 0.7$ are presented. *TPR IFS* is even better (and with lower standard deviation) than it was for asymmetric

Table 4: Results for Wine, $\alpha = 0.7$, asymmetric granulation

no class		Acc FS	Acc IFS	TPR FS	TPR IFS	FPR FS	FPR IFS
1	average	96.5	98.5	0.92	0.99	0.01	0.02
	standard deviation	1.8	1.1	0.05	0.02	0.01	0.01
2	average	94.4	94.0	0.86	0.97	0	0.08
	standard deviation	2.6	2.0	0.06	0.03	0.01	0.04
3	average	97.5	98.7	0.91	0.97	0	0.01
	standard deviation	0.8	1.2	0.03	0.02	0	0.01

Table 5: Results for Wine, $\alpha = 0.7$, symmetric granulation

no class		Acc FS	Acc IFS	TPR FS	TPR IFS	FPR FS	FPR IFS
1	average	96.4	96.3	0.92	0.99	0.01	0.05
	standard deviation	1.7	1.7	0.06	0.01	0.01	0.03
2	average	94.3	95.2	0.86	0.99	0	0.07
	standard deviation	1.8	1.7	0.05	0.01	0	0.03
3	average	99.0	98.7	0.96	1	0	0.02
	standard deviation	1.1	1.1	0.04	0	0	0.02

granulation (0.99 for classes 1 and 2, 1 – for class 3; previously (Table 4) it was: 0.99 for class 1, 0.97 for classes 2 and 3) but at cost of increasing values of *FPR IFS* (0.05 instead of 0.02 for class 1, 0.07 instead of 0.08 for class 2 – so in this case for symmetric granulation the result is even better, and 0.02 instead of 0.01 for class 3).

In the case of the two examined benchmark data bases, intuitionistic fuzzy classifier recognizes better relatively smaller classes that fuzzy classifier, and symmetric granulation make it possible to see even better (than asymmetric granulation) relatively smaller classes. But accuracy of recognizing all classes is in general lower for symmetric granulation.

4 Conclusions

A simple intuitionistic fuzzy classifier was tested on imbalanced and overlapping data. Results obtained confirm that the intuitionistic fuzzy classifier fulfills our main demand, i.e., ”sees” better relatively smaller classes. The results are better than for a fuzzy classifier. We may pay for it in lower accuracy of recognizing all instances because bigger classes might be seen worse. But it is not a rule – sometimes both relatively smaller class and bigger classes are recognized better by intuitionistic fuzzy classifier than by the counterpart fuzzy classifier.

Acknowledgments Partially supported by the Ministry of Science and Higher Education Grant Nr N N519 384936.

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The papers presented in this Volume 2 constitute a collection of contributions, both of a foundational and applied type, by both well-known experts and young researchers in various fields of broadly perceived intelligent systems.
It may be viewed as a result of fruitful discussions held during the Tenth International Workshop on Intuitionistic Fuzzy Sets and Generalized Nets (IWIFSGN-2011) organized in Warsaw on September 30, 2011 by the Systems Research Institute, Polish Academy of Sciences, in Warsaw, Poland, Institute of Biophysics and Biomedical Engineering, Bulgarian Academy of Sciences in Sofia, Bulgaria, and WIT - Warsaw School of Information Technology in Warsaw, Poland, and co-organized by: the Matej Bel University, Banska Bystrica, Slovakia, Universidad Publica de Navarra, Pamplona, Spain, Universidade de Tras-Os-Montes e Alto Douro, Vila Real, Portugal, and the University of Westminster, Harrow, UK:

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The consecutive International Workshops on Intuitionistic Fuzzy Sets and Generalized Nets (IWIFSGNs) have been meant to provide a forum for the presentation of new results and for scientific discussion on new developments in foundations and applications of intuitionistic fuzzy sets and generalized nets pioneered by Professor Krassimir T. Atanassov. Other topics related to broadly perceived representation and processing of uncertain and imprecise information and intelligent systems have also been included. The Tenth International Workshop on Intuitionistic Fuzzy Sets and Generalized Nets (IWIFSGN-2011) is a continuation of this undertaking, and provides many new ideas and results in the areas concerned.

We hope that a collection of main contributions presented at the Workshop, completed with many papers by leading experts who have not been able to participate, will provide a source of much needed information on recent trends in the topics considered.

ISBN-13 9788389475411