Analyzing Classifier Hierarchy Multiclassifier Learning

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Abstract. Classifier combination falls in the so called machine learning area. Its aim is to combine some classification paradigms in order to improve the individual accuracy of the component classifiers. Classifier hierarchies are an alternative among the several methods of classifier combination. In this paper we present new results about a recently proposed hierarchy construction method. Experiments have been carried out over 42 databases from the UCI repository, showing an improvement over the performance of the base classifiers.

Keywords: Classifier combination, hierarchy of classifiers, data mining.

1 Introduction

In the last years different approaches to improve the performance of a single classifier have been studied in the machine learning community, being one of them the combination of classifiers. There are very different manners to combine classifiers, most of which have been found to improve accuracy over single classifiers [3]. Several approaches have been studied, among them: bagging [5], that uses more than one model of the same paradigm in order to reduce errors; boosting [6], in which a different weight is given to different training examples looking for a better accuracy; bi-layer classifiers [4] where several models from different paradigms are combined in a parallel mode, using the individual decision of each one as predictor variable for a new classifier which takes the final decision; there are some other combination approach in serial or semi-parallel architectures [7]. Other way is to build a classifier hierarchy, constructed in the shape of a tree. This hierarchy could be learned in a recursive mode, using a top-down approach to select the classifier of each of the edges, taking into account the data.

In this paper we continue the work presented in [8], where the authors define a new hierarchy construction method and make a search in the space of all possible

hierarchies by means of a genetic algorithm. Here we show that good results could also be achieved by a pure random search. Our results have been obtained over 42 databases from the UCI repository, three times as much databases than in the original paper, where only 14 were analyzed.

The rest of the paper is organized as follows: Section 2 gives a brief introduction to the hierarchical model of combination of classifiers. In section 3 how to construct an actual model from a hierarchy of classifiers is described. Section 4 is devoted to the experimental setup and results obtained, while the final section presents the conclusions and points out the future work.

2 Hierarchy of Classifiers

As mentioned above, the combination of multiple classifiers has been intensively studied with the aim of improving the individual accuracy of individual components. It has been shown that in many domains an ensemble of classifiers outperforms any of its single components.

According to the architecture used to combine different single classifiers, Lu [11] cites three possible configurations: cascaded, parallel and hierarchical. The characteristics of these architectures are:

- In a *cascaded system*, the classification results generated by a classifier are often used to direct the classification processes of successive classifiers. The main problem in this method is that errors made by previous classifiers are not recoverable by the successive classifiers.
- In a *parallel system*, there is a true integration of knowledge of different sources, generated independently. If the decision process is well designed, the overall system may reach peak performance.
- In a *hierarchical system*, the control strategy is a combination of cascaded and parallel processing.

Fig. 1. A hierarchy of classifiers in a Yes-No problem. In this example there are three different classifiers that induce three kinds of models (Model 1 to Model 3).

The approach analyzed in this paper falls within the hierarchical model [12].

A possibility to form this hierarchy is to arrange the single classifiers in a tree. In such a representation, a new case runs the following path: starting at the root node, the instance is classified according to the model associated to that node; then a test is performed on the outcome of the model and, according to the result, a branch is selected and the process continues until the case reaches a leaf, and the outcome of the model at this stage is returned. See Figure 1 for an example.

The idea behind this procedure is that the mistakes a classifier makes can be the input to another classifier, in such a way that this one could discover some patterns in the mistakes. Iteration of this procedure leads to a hierarchy (or tree) of classifiers.

3 Induction of Individual Classifiers in a Single Hierarchy

Given a hierarchy schemata, the classifiers corresponding to each node should be induced. To do that, we apply a recursive algorithm similar to the so called Top Down Induction of Decision Trees [14] as shown in Figure 2.

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Classifier learning(DB, C, H)
  Input: a Database DB containing  $m$  cases for a classification
        problem having  $C$  possible categories, and a hierarchy  $H$ .
  Output: The classification model for each of the node
         in the hierarchy.

  Learn the classifier of the root node
  from the whole Database DB.
  For each of the  $c$  possible class values,
  construct a database  $DB(c=i)$ 
  Initialize  $DB(c=i)$  to an empty set for all the classes.
  Using a validation technique, do the following
  for the cases in DB:
    Classify the case using the root model.
    Let  $j$  be the classification obtained
    Add the case to  $DB(c=j)$ 
  Call recursively to this "Classifier Learning" algorithm
  for each of the nodes pending from the root node,
  using as input the obtained databases and the
  corresponding subpart of the hierarchy
Classifier Learning

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Fig. 2. Classifier induction process for a given hierarchy

The following example will help to understand this process.

Given the hierarchy in Figure 1 and supposing that the hierarchy is built with three classifier paradigms ($I = 3$), for a two-class problem. Let us denote the two classes as *Yes*, *No*. It is necessary to build the classifier model for each of the nodes in the tree that forms the hierarchy. Let us name *Example.data* the datafile where all the available instances corresponding to our classification problem are collected. The procedure is as follows:

- The classifier in the root node of the hierarchy is constructed using all the cases in *Example.data*
- The classifier in every node different from the root is constructed in the following way:
 - Get the database which was used to build the classifier at the parent node.
 - Divide the database into n folds of the same size.
 - For each fold,
 - classify each case in the fold using the model induced by the remaining $n-1$ folds.
 - If *class of case = yes*, add it to *Exampleyes.data* else add it to *Exampmeno.data*.
 - Induce the corresponding models using the obtained databases.
 - If the node is reached from the parent node through a *Yes* edge, then use *Exampleyes.data* to build the model associated at that node. If it is not (that is, if the node is reached through a *No* edge), use *Exampmeno.data* to build the model.
 - If all the cases are classified as *Yes* or *No*, create a leaf at that node.

In our setup the number of folds is 7, according to the results shown in [9].

4 Experimental Setup and Results

In order to evaluate the performance of the proposed approach, we have carried out an experiment over 42 databases from the UCI repository [13]. In our experimental setup we have chosen four base classifiers: ID3 [14], C4.5 [16], Naive Bayes [15] and IB1 [1], available in *MCC++* libraries [2].

The criterion to define the fitness of a hierarchy is the performance of a 5×2 cross validation over each database [10]. In Table 1 are presented the accuracies of the four base classifiers. In boldface is shown the best of all four.

As a first approach, we have chosen 200 random three-level hierarchies, as well as 500 random four-level hierarchies. In Table 2 the best accuracy obtained by a hierarchy is shown under the label *Best depth 3* and *Best depth 4*, for hierarchies of three and four levels respectively. In *Relative best base* the number of hierarchies found better than the best of the base classifiers is shown under the *Wins* label, along with the number of hierarchies that tie, under the *Ties* label. From these tables it is observed that, when restricted to hierarchies of three levels, a best results than the best case classifier is obtained in 23 out of 42 databases, while there are 16 ties and only in three cases the best hierarchy performs worse than the best base classifier. When evaluating the hierarchies of four levels, the results are similar, though a bit better (+23 = 18 -1).

Other experiment has been carried out, this time evaluating all possible two-level hierarchies in the 26 two-classes problems out of the 42 original databases. As there are four different possibilities in the root node (the four base classifiers) and five in each of the two branches corresponding to each class (the four base

Table 1. Accuracies over the databases used in this experiment

<i>Database</i>	<i>NB</i>	<i>Ib</i>	<i>Id3</i>	<i>C4.5</i>
Anneal	93.01	97.35	98.57	98.13
Australian	76.84	80.96	80.96	84.58
Auto	55.13	65.26	66.24	62.34
Balance Scale	89.95	82.30	78.18	78.98
Banding	75.71	76.05	74.20	78.24
Breast	95.91	95.65	94.42	94.31
Cars	98.88	98.98	96.89	96.38
Chess	87.15	92.87	98.87	99.00
Churn	88.57	83.52	91.54	94.12
Cleve	82.97	77.49	73.00	76.97
Corral	83.91	91.09	96.41	92.19
Crx	77.45	81.57	80.70	84.96
Diabetes	75.31	69.66	69.43	72.71
Echocardiogram	71.90	56.18	61.82	63.96
Flare	80.88	80.88	80.69	82.33
German	74.46	69.22	69.08	70.92
Glass	50.28	64.95	64.95	64.21
Glass2	62.58	76.81	77.28	76.08
Hayes Roth	70.62	63.62	84.37	83.75
Heart	82.30	74.44	74.74	75.56
Hepatitis	85.40	80.38	74.84	78.31
Horse-colic	78.97	73.64	78.42	85.54
Hungarian	84.22	79.39	77.21	79.86
Hypothyroid	97.80	96.96	98.62	99.15
Iris	95.47	94.93	94.67	94.13
Lenses	64.17	69.17	75.00	69.17
Liver-disorder	56.46	59.13	60.17	59.94
Lymphography	78.38	79.73	76.62	78.92
Mushroom	99.67	100.00	99.98	99.98
Parity5+5	47.05	51.05	63.87	53.71
Pima	75.39	69.24	69.56	71.59
Solar	66.13	65.63	68.36	71.64
Sonar	68.85	83.08	72.98	70.96
Splice	95.22	72.51	89.40	92.52
ThreeOf9	79.53	90.62	96.60	95.00
Tic-tac-toe	70.31	95.64	82.42	81.38
Tokyo1	88.53	91.43	89.72	91.16
Vehicle	45.41	68.13	69.67	70.50
Vote	90.20	92.55	93.52	95.08
Vote1	87.17	89.52	87.08	87.95
Wine	96.74	94.49	88.76	87.75
Zoo	80.03	94.26	92.48	90.32

Table 2. Accuracy of the best hierarchy along with the number of hierarchies outperforming it for several depths

Database	Depth 3			Depth 4		
	Best accuracy	Relative best base		Best accuracy	Relative best base	
		Wins	Ties		Wins	Ties
Anneal	98.73	6	4	98.73	12	13
Australian	84.93	4	0	85.01	8	4
Auto	64.78*	0	0	65.95*	0	0
Balance Scale	89.95	0	2	89.95	0	4
Banding	79.41	3	0	78.82	3	0
Breast	96.65	12	0	96.68	39	3
Cars	99.18	36	48	99.18	70	128
Chess	99.07	16	1	99.14	11	6
Churn	94.12	0	4	94.12	0	3
Cleve	83.04	2	1	82.97	0	10
Corral	96.41	0	17	96.41	0	31
Crx	85.54	7	1	85.30	6	7
Diabetes	75.31	0	12	75.70	1	5
Echocardiogram	71.90	0	4	71.90	0	9
Flare	82.70	17	0	82.81	56	10
German	74.60	2	1	74.64	2	5
Glass	65.98	2	0	65.14	1	0
Glass2	78.65	8	0	78.41	12	3
Hayes Roth	84.63	3	0	84.88	11	0
Heart	82.30	0	2	82.30	0	5
Hepatitis	85.40	0	3	85.40	0	4
Horse-colic	85.54	0	1	85.54	0	4
Hungarian	84.22	0	3	84.22	0	4
Hypothyroid	99.15	0	2	99.15	0	8
Iris	96.00	11	10	96.00	11	12
Lenses	75.00	0	16	75.00	0	63
Liver-disorder	63.83	74	1	63.65	173	10
Lymphography	80.68	7	3	81.35	22	8
Mushroom	100.00	0	58	100.00	0	132
Parity5+5	63.87	0	3	63.87	0	2
Pima	75.52	1	0	75.96	2	8
Solar	71.51*	0	0	71.64	0	5
Sonar	83.08	0	2	83.08	0	5
Splice	95.26	2	1	95.26	4	1
ThreeOf9	96.64	2	3	96.68	3	6
Tic-tac-toe	95.74	5	36	95.82	5	75
Tokyo1	91.93	9	0	91.95	18	1
Vehicle	70.35*	0	0	70.50	0	1
Vote	95.40	9	2	95.54	22	9
Vote1	89.79	2	3	89.98	4	7
Wine	96.74	0	43	96.74	0	132
Zoo	94.26	0	49	94.26	0	129

Table 3. Results over the 26 two-class databases using two level classifiers

<i>Database</i>	<i>Best result</i>	<i>Root classifier</i>	<i>Best base classifier</i>
Australian	84.43	c4.5	c4.5 (84.58)
Banding	78.74	nb	c4.5 (78.24)
Breast	96.68	ib	ib (95.91)
Chess	99.07	c4.5	c4.5 (99.00)
Churn	94.10	c4.5	c4.5 (94.12)
Cleve	82.77	nb	nb (82.97)
Corral	96.41	id3	id3 (96.41)
Crx	85.65	id3	c4.5 (84.96)
Diabetes	75.08	nb	nb (75.31)
Echocardiogram	71.44	c4.5	nb (71.90)
Flare	82.66	c4.5	ib (82.33)
German	74.60	nb	nb (74.46)
Glass2	78.17	c4.5	id3 (77.28)
Heart	80.96	nb	nb (82.30)
Hepatitis	84.49	nb	nb (85.40)
Horse-colic	85.38	c4.5	c4.5 (85.54)
Hungarian	83.67	nb	nb (84.22)
Hypothyroid	99.15	c4.5	c4.5 (99.15)
Liver-disorder	63.65	id3	nb (60.17)
Mushroom	100.00	ib	ib (100.00)
Pima	75.34	nb	nb (75.39)
Sonar	82.40	ib	ib (83.08)
Tic-tac-toe	95.64	ib	ib (95.64)
Tokyo1	91.91	c4.5	nb (91.43)
Vote	95.40	c4.5	c4.5 (95.08)
Vote1	89.61	nb	ib (89.52)

classifiers and the possibility of being a leaf), a total of $5 \times 5 \times 4 = 100$ hierarchies have been studied. Results are shown in Table 3. *Best result* stands for the best result of a no-simple hierarchy. *Root classifier* is the classifier at the root node of the previously cited hierarchy. And *Best base classifier* is the best performing among the base classifier along with its accuracy. From this table we observe that the root node of the best no-simple classifier matches the best base classifier in 17 out of 26 databases, suggesting that a greedy search could be of interest, instead of simply a random search or something more demanding as a genetic search. It has also to be noticed that, even in the cases (9 out of 26 databases) where the root classifier in the best hierarchy does not match with the best base classifier, there are other hierarchies which outperform that best single classifier, using that classifier as root node.

5 Conclusions and Future Work

New results about a recently proposed hierarchy construction method have been presented in this paper. Experiments have been carried out over 42 databases

from the UCI repository, with hierarchies of two, three and four levels. Our results with a random search over three and four levels suggest that it could be possible to implement a greedy search instead of a genetic search. The small improvement obtained with four levels over the three levels hierarchies suggest that three could be the ideal number of levels in a hierarchy. Experiments over two level hierarchies show that usually the root classifier in the best no-simple hierarchy matches with the best base classifier, suggesting the convenience of starting the greedy search with the best base classifier as root node of the hierarchy.

Future work involves more detailed research on greedy search, with problems with more of two classes, as well with three or more level hierarchies. Research about the best number of levels of hierarchies are going to be conducted too.

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