Appendix: A scalable pairwise class interaction framework for multidimensional classification

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1 Additional Results for the manuscript.

This document is intended to be a compilation of additional experiments performed during the evaluation of our method and/or during the reviewing process of the manuscript. The original work is a paper submitted to the IJAR journal currently on review process.

Following the same experimental scheme we will show additional results for execution time and both accuracy measures: global and Hamming accuracy. Please refer to the original manuscript for a detailed description of our experimental environment.

1.1 Experiment: FMC using TAN classifier as base-classifier

In the original paper, the approaches are tested by using the A1DE classifier and the naive Bayes classifier. These two models were selected according to their different properties: The first one will obtain much richer predictions but at the expense of efficiency whereas the second one will be much more efficient but with poorer results.

In order to contrast this decision we conducted additional experiments by using other choices of probabilistic base classifiers. More concretely we tested the TAN classifier in several databases. The results showed that, in general, it performed less efficiently than AODE but with poorer results. The next tables show the results for global accuracy and Hamming accuracy respectively using the TAN classifier.

method	emotions	enron	genbase	yeast
FSBDeu-A1DE	**0.3253**	0.1263	0.9608	**0.1994**
FSBDeu-NB	0.2933	0.1181	0.9562	0.1684
full-A1DE	0.3017	**0.1269**	**0.9623**	0.1850
full-NB	0.2831	0.1105	0.9562	0.1486
FSBDeu-TAN	0.3101	0.1246	0.9587	0.1937
full-TAN	0.2851	0.1170	0.9398	0.1901

method	emotions	enron	genbase	yeast
FSBDeu-A1DE	**0.7987**	0.9508	0.9985	0.7937
FSBDeu-NB	0.7846	0.9361	0.9983	0.7792
full-A1DE	0.7960	**0.9511**	**0.9986**	0.7939
full-NB	0.7835	0.9309	0.9984	0.7770
FSBDeu-TAN	0.7951	0.9482	0.9983	**0.7945**
full-TAN	0.7867	0.9412	0.9976	0.7834

As we can observe the TAN performance is between A1DE and NB. In the next table we show the runtime in seconds, as we can observe the TAN experiments are by far less efficient than the A1DE. We must remark that the implementation of the TAN classifier in Weka is very inefficient, whereas the A1DE classifier has been optimized.

method	emotions	enron	genbase	yeast
FSBDeu-A1DE	**1.4419**	548.1504	16.6185	**15.6935**
FSBDeu-NB	1.4842	**543.3404**	**16.4544**	18.9105
FSBDeu-TAN	101.9720	8334.7410	54.4400	8365.8470
full-A1DE	2.9314	8007.7372	148.8509	34.1011
full-NB	2.5051	8047.8660	141.5329	33.2470
full-TAN	255.5810	96152.6500	484.3000	12860.4200

1.2 Continuous Naive Bayes and A1DE

In the paper we describe a novel approach for supervised discretization in our FMC framework that can be extended to almost any transformation based multi-label classifier. With this method we discretize the training data for each individual base classifier model which corresponds with a single class classification problem. For that we apply the well known MDL discretization algorithm. This is a great advantage as there are not standardized supervised discretization methods for multilabel problems.

Although they are not included in the paper we also performed our experiments by avoiding the discretization of the continuous variables, for that we used versions of the base classifiers capable of dealing with both categorical and numerical data. More concretely, naive Bayes is easily adaptable to use Gaussian distributions and kernel methods to model the different attribute distributions. In the case of A1DE, there are two proposed algorithms, GAODE and HAODE, that allow Gaussian distributions to be used in the original A1DE approach.

We conducted several experiments by instantiating our FMC framework with these base classifiers, however the results were worse than the discretized versions as we can observe in the following table. This bad result can be attributed to a bad adjust of the continuous predictive attributes to the distributions used to model them.

Global Acc

classifier	birds	CAL500	CLEF14	emotions	scene	yeast
FMC-A1DE	0.4473		0.3613	0.3051	0.6465	
FMC-GAODE				0.2577	0.3930	0.1436
FMC-HAODE				0.2968	0.4902	0.1444
FMC-NB	0.3075		0.1059	0.2932	0.4487	0.1432
FMC-NBG			0.0945	0.2561	0.4055	0.1188
FMC-tree-A1DE	0.4318		0.4941	0.2850	0.6111	0.1659
FMC-tree-GAODE		0.0000		0.2190	0.3021	0.1245
FMC-tree-HAODE	0.2112	0.0000		0.2614	0.3656	0.1299
FMC-tree-NB	0.2920	0.0000	0.1740	0.2798	0.4657	0.1216
FMC-tree-NBG		0.0000	0.1261	0.2191	0.2834	0.1022
FMC-tree-NBK		0.0000		0.2797	0.5106	0.1423

Hamming Acc

classifier	birds	CAL500	CLEF14	emotions	scene	yeast
FMC-A1DE	0.9408		0.8419	0.8007	0.9126	
FMC-GAODE				0.7759	0.8396	0.7559
FMC-HAODE				0.7993	0.8687	0.7482
FMC-NB	0.8772		0.7232	0.7841	0.8808	0.7626
FMC-NBG			0.6802	0.7640	0.8502	0.7329
FMC-tree-A1DE	0.9302		0.8853	0.7909	0.9033	0.7784
FMC-tree-GAODE		0.6987		0.7594	0.8239	0.7298
FMC-tree-HAODE	0.9172	0.7620		0.7799	0.8499	0.7282
FMC-tree-NB	0.8639	0.8592	0.7667	0.7824	0.8658	0.7544
FMC-tree-NBG		0.7160	0.7369	0.7542	0.8253	0.7048
FMC-tree-NBK		0.8165		0.7742	0.8834	0.7382

References

Flores, M. Julia, et al. "GAODE and HAODE: two proposals based on AODE to deal with continuous variables." Proceedings of the 26th annual international conference on machine learning. ACM, 2009.

2 Preliminary comparison with other state-of-art classifiers

2.1 Preliminary comparison between FMC and M-CTBN

We performed a briefly comparison between the M-CTBN method and our FMC, however the efficiency of this method is in a different scale than ours and was only tested for the smaller datasets, obtaining an execution time that hit our wall-time. We show the preliminary results for global accuracy on the left and hamming accuracy on the right.

method	emotions	scene	yeast
FSBDeu-A1DE	0.3253	0.6581	0.1994
full-A1DE	0.3017	0.6597	0.1850
MCTBN	0.2949	0.6593	0.4501

method	emotions	scene	yeast
FSBDeu-A1DE	0.7987	0.9117	0.7937
full-A1DE	0.7960	0.9122	0.7939
MCTBN	0.7743	0.9074	0.8417

The next table contains the runtime for both algorithms, showing the huge difference we mentioned before:

method	emotions	scene	yeast
FSBDeu-A1DE	5	59	75
full-A1DE	8	59	202
MCTBN	3304	22618	31902

References

C. Hong, I. Batal, and M. Hauskrecht. A mixtures-of-trees framework for multi-label classification. ACM International Conference on Information and Knowledge Management (CIKM 2014), Shanghai, China. November 2014.
Code: `https://github.com/charmgil/M-CTBN`

2.2 Preliminary comparison between FMC and BCC

We performed a preliminary experiment by using the Bayesian Chain Classifier algorithm. However the code of this proposal was only prototypical and the results obtained were not optimized, as it comparison with the ones reported in the original paper disagrees. We will update these results when newer versions of the code will be released. The next tables show global accuracy and Hamming accuracy respectively.

method	birds	CAL500	CLEF14	emotions	enron	genbase	medical	scene	tmc2007	yeast
ECC-NB	0.4562	**0.0000**	0.1033	**0.3001**	**0.1234**	**0.9728**	0.6205	0.3403	0.2206	0.1643
FSBDeu-NB	0.4315	**0.0000**	**0.1755**	0.2933	0.1181	0.9562	**0.6227**	**0.5069**	**0.2336**	**0.1684**
full-NB	**0.4658**	**0.0000**	0.1383	0.2831	0.1105	0.9562	0.6227	0.5052	0.2320	0.1486
BCC	0.0404	**0.0000**	-	0.2024	0.0012	0.2734	0.2648	0.1317	0.1429	0.0935

Hamming acc

method	birds	CAL500	emotions	enron	genbase	medical	scene	tmc2007	yeast
full-NB	**0.9449**	**0.8619**	0.7835	0.9309	0.9984	**0.9888**	0.8853	**0.9302**	0.7770
FSBDeu-NB	0.9347	0.8616	0.7846	**0.9361**	0.9983	0.9884	**0.8858**	0.9299	0.7792
BCC	0.6976	0.6818	0.7462	0.7813	0.9658	0.9746	0.7435	0.8861	0.6984
ECC-NB	0.9442	0.8526	**0.7909**	0.9324	**0.9989**	0.9888	0.8548	0.9267	**0.7812**

References

Zaragoza, Julio H., et al. "Bayesian chain classifiers for multidimensional classification." IJCAI. Vol. 11. 2011.