Analyzing the Separability Matrix for ECOC coding

Miguel Angel Bautista, Sergio Escalera, Xavier Baró, Oriol Pujol

Computer Vision Center, Universitat Autònoma de Barcelona, 08193 Cerdanyola, Spain
Dept. Matemàtica Aplicada i Anàlisi, UB, Gran Via 585, 08007, Barcelona, Spain
{mbautista,sescalera,xavier.baro,oriol.pujol}@cvc.uab.es

UNIVERSITAT DE BARCELONA

Centre de Visió per Computador

Abstract

Error Correcting Output Codes (ECOC) have demonstrated to be a powerful tool to treat multi-class categorization problems. Nevertheless, state-of-the-art standard designs do not benefit from error-correcting principles for a particular multi-class data. In this poster, we introduce a novel tool to analyze the correction capabilities of ECOC designs, as well as a new coding technique that shows great performance results.

1. Error Correcting Output Codes (ECOC)

•A common way to deal with Multi-class Object Categorization problems is by means of a divide- and-conquer approach. In this scope, ECOC have been applied with successful results.

•Given a set of *N* classes to be learnt in an ECOC framework, *n* different bi-partitions (two groups of classes) are formed, and *n* binary problems (dichotomizer) are trained.

•A codeword of length n is obtained for each class, where each position (bit) of the code corresponds to a response of a given dichotomizer (coded by +1 or -1 according to their class set membership).

•Arranging the codewords as rows of a matrix, we define a coding matrix *M*, where $M \in \{-1, +1\}^{N \times n}$ in the binary case. In the case of the ternary symbol-based ECOC, the cod- ing matrix becomes $M \in \{-1, 0, +1\}^{N \times n}$ where the symbol zero means that a particular class is not considered for a given classifier.

•During the decoding process, applying *n* binary classifiers, a code *x* is obtained for each data sample ρ in the test set.

2. The Separability Matrix

•The Separabilty Matrix *S* containts the pairwise distance δ between codes. In Figure 1 we show an example for the coding and separability matrices for a One Vs. All and Compact coding designs.

•As it is shown the Separability matrix does not provide special information for predefined ECOC coding, since they have equidistant codes. Nevertheless, with this tool the correction capabilties between classes in non predefined approaches can be analyzed.

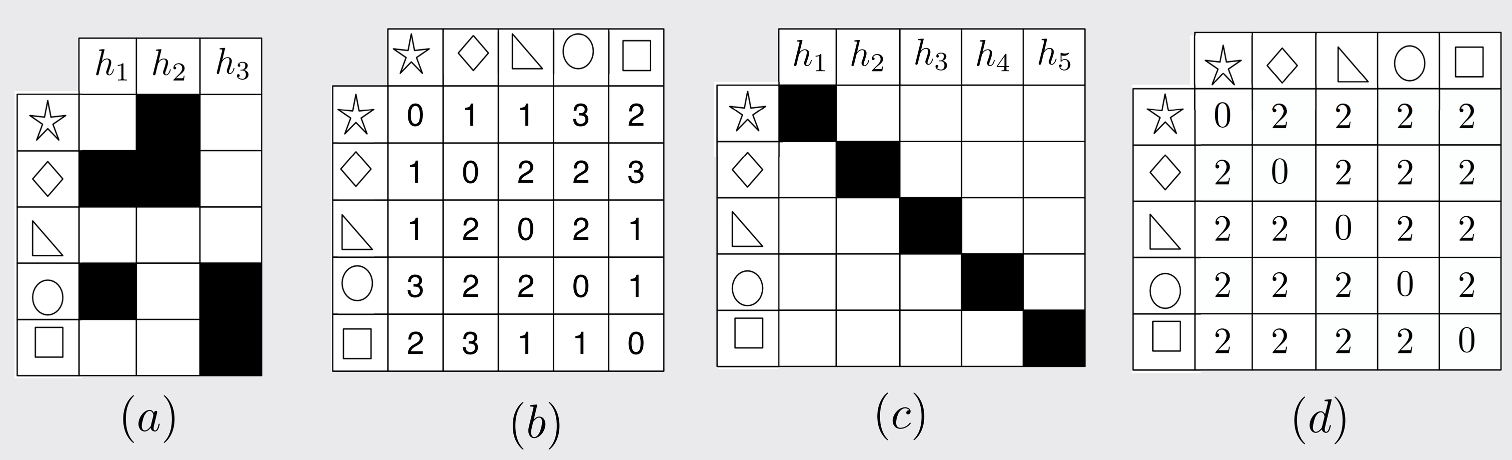

Figure 1. (a) Compact ECOC coding matrix. (b) Separability Matrix of a Compact ECOC. (c) One vs. All coding matrix. (d) Separability matrix of One vs. All coding.

•As it is shown the Separability matrix does not provide special information for predefined ECOC coding, since they have equidistant codes. Nevertheless, in problem-dependent designs the Sepabilty matrix acquires a great value since it helps to identify those codes that are prone to have more errors due to a lack of error correcting capabilities.

3. The CSE Coding Algorithm

•The CSE coding algorithm is an iterative algorithm that computes an extension matrix of a given ECOC coding matrix.

•This algorithm uses both the Separabilty and Confusion matrices to compute an extension matrix that focuses the error correcting capabilities on those codes that are more prone to be confused.

• With this algorithm we can compute an ECOC matrix that yet having a reduced code length can outperform state-of-the-art designs since it focuses the correction capabilities on certain classes.

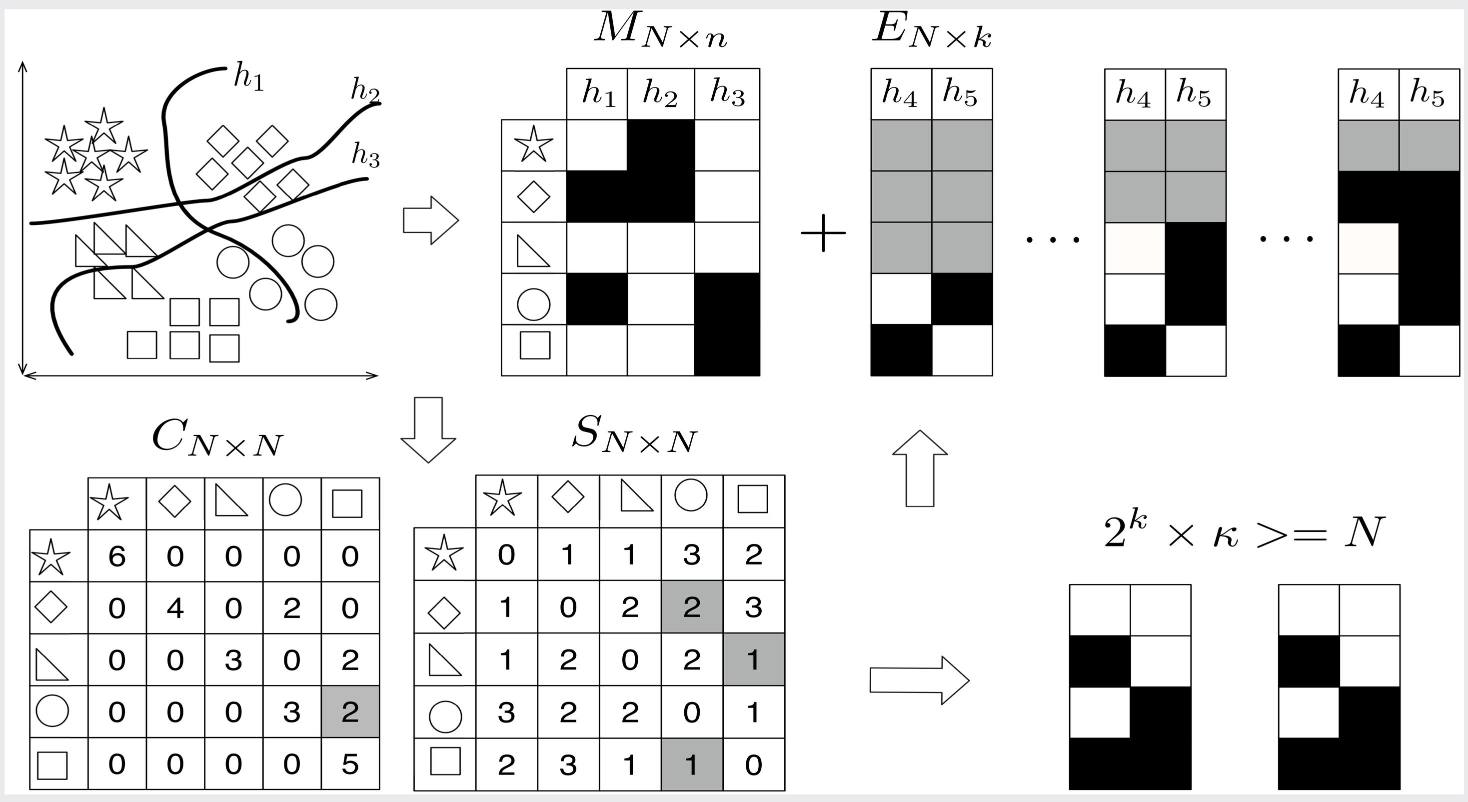

Figure 2. Example of the CSE coding algorithm in a 5-class toy problem.

4. Experiments and results

The first bench of experiments consists of seven muti-class problems extracted from the UCI Machine Learning Repository. In addition, we test our methodology over 3 challenging Computer Vision multi-class problems. First, we classify 70 visual object categories from the MPEG dataset. Then, 50 classes of the ARFace database are classified. Finally, we test our method in a real traffic sign categorization problem consisting of 36 traffic sign classes.

	One vs. All ECOC		CSE ECOC $\varrho = 3$		CSE ECOC $\varrho = 5$		Dense Random ECOC	
Data set	Perf.	Classif.	Perf.	Classif.	Perf.	Classif.	Perf.	Classif.
Vowel	55.0±10.5	11	66.9±7.8	9.2	**69.8±6.3**	10.6	67.9±8.3	11
Yeast	41.0±7.3	10	54.7±11.8	5.7	53.0±9.3	9.5	**54.9±6.4**	10
Ecoli	**78.9±3.5**	8	76.4±4.4	7	78.6±3.9	7.4	72.1±2.7	8
Glass	51.6±10.2	7	**55.5±7.6**	6	52.7±8.4	3	42.8±11.02	7
Segment	**97.3±0.7**	7	96.9±0.8	6.6	96.6±1.0	6.2	96.6±1.3	7
Derma	97.1±1.2	6	**97.1±0.9**	5.2	95.9±1.2	3	95.7±0.8	6
Vehicle	80.1±4.0	4	**81.1±3.5**	3	70.6±3.4	3	81.1±3.6	4
MPEG7	83.2±5.1	70	88.5±4.5	15	89.6±4.9	20.4	**90.0±6.4**	70
ARFaces	76.0±7.22	50	80.7±5.2	13.8	84.6±5.3	20.2	**85.0±6.3**	50
Traffic	91.3±1.1	36	95.7±0.92	12.2	**96.6±0.8**	19	93.3±1.0	36
Rank & #	3.0	20.8	**2.2**	**8.8**	2.3	10.3	2.5	20.8

5. CONCLUSIONS

In conclusion, results show that the proposed method outperforms the One vs. All standard cod- ing design in most cases, using far less number of dichotomizers. This is caused by the fact that the proposed algorithm focus the correcting capa- bility in those classes more prone to be confused, and thus, less redundancy is needed. Nevertheless, when comparing Dense Random coding with our method in terms of performance, no significance is found since both methods have a comparable rank.

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