Centre de Visió per Computador

Coding and Decoding Design of ECOCs for Multi-class Pattern and Object Recognition

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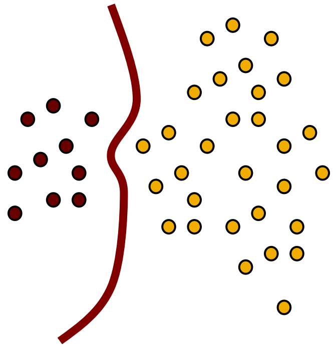
Layout

- Introduction
- Error-Correcting Output Codes (ECOC)
  - Coding
  - Decoding
- Applications
- Conclusions

Classifiers

- Main families of classifiers
  - Similarity Maximization Methods → Similarity measure
  - Probabilistic Methods → Bayesian Decision Theory
  - Geometric Classifiers → Decision boundaries **[Jain00]**

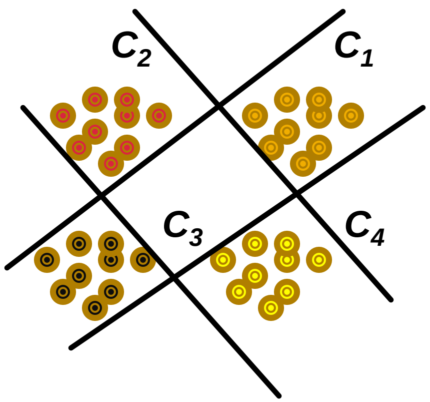


- Multi-class versus binary classification
  - Discriminative classifiers are binary-defined by default
  - Most discriminative multi-class classifiers are defined as a combination of binary problems

[Jain00] Anil K. Jain, Robert P.W. Duin, Jianchang Mao, Statistical Pattern Recognition: A Review, IEEE Transactions on Pattern Analysis and Machine Intelligence, 2000.

Combining strategies

- Multi-class as a combination of binary classifiers (dichotomizers)
  - One-versus-all



c_1 vs $c_2 c_3 c_4$

c_2 vs $c_1 c_3 c_4$

c_3 vs $c_1 c_2 c_4$

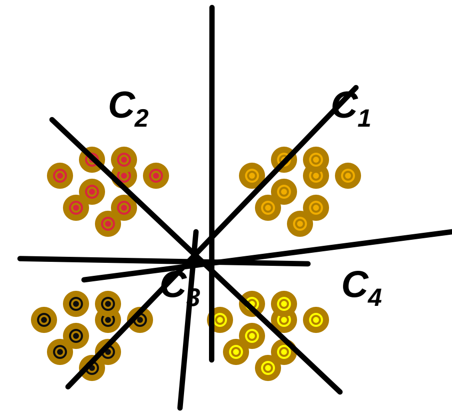
c_4 vs $c_1 c_2 c_3$

One-versus-one (pairwise)

c_1 vs c_2 c_2 vs c_3

c_1 vs c_3 c_2 vs c_4

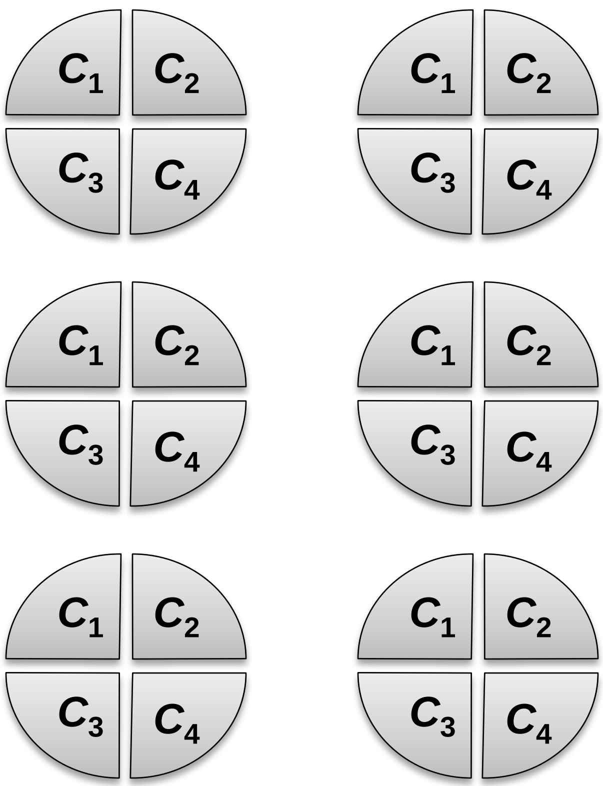
c_1 vs c_4 c_3 vs c_4



  - Error-Correcting Output Codes

[Dietterich95] Thomas G. Dietterich, Ghulum Bakiri, Solving Multiclass Learning Problems via Error-Correcting Output Codes, Journal of Artificial Intelligence Research, 1995

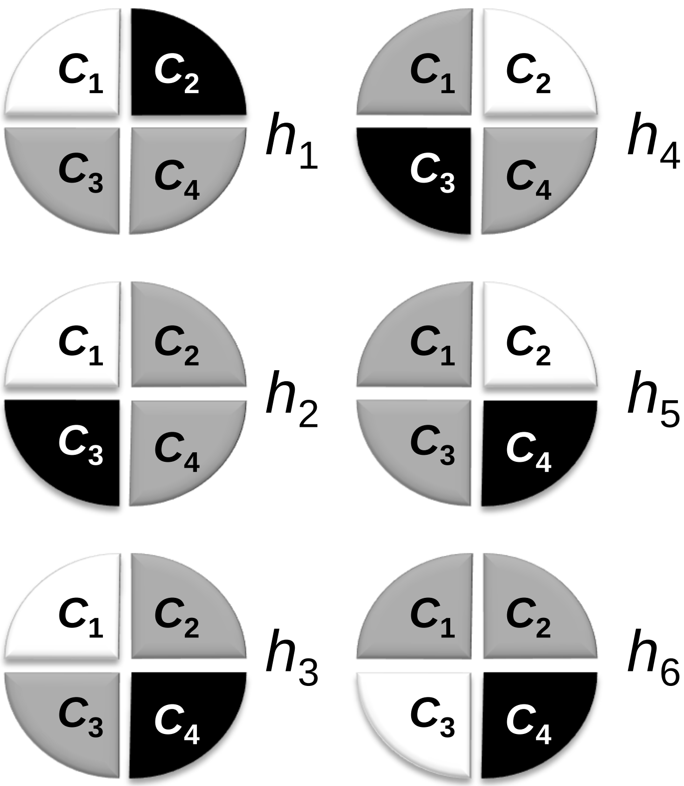
Error-Correcting Output Codes

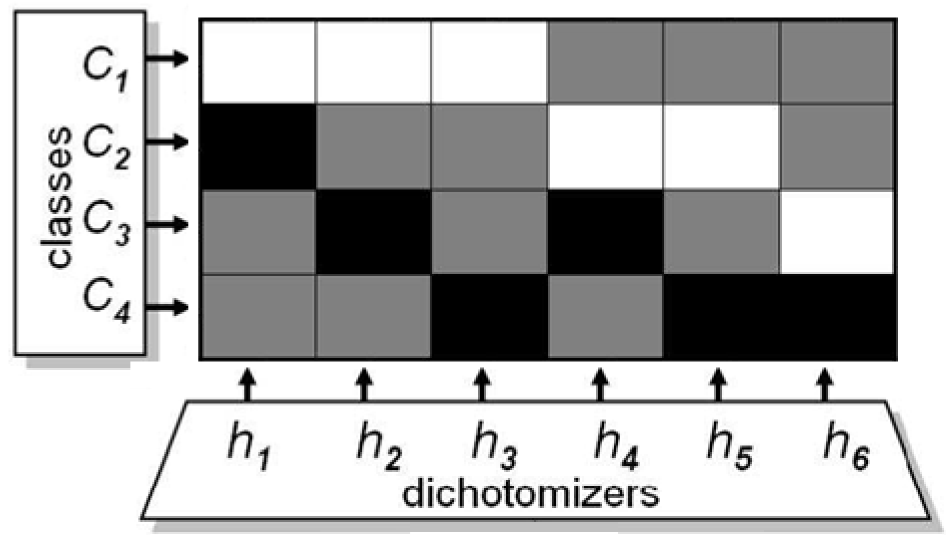


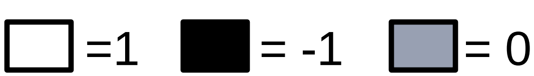
Error-Correcting Output Codes - **Coding**

Training

one-versus-one



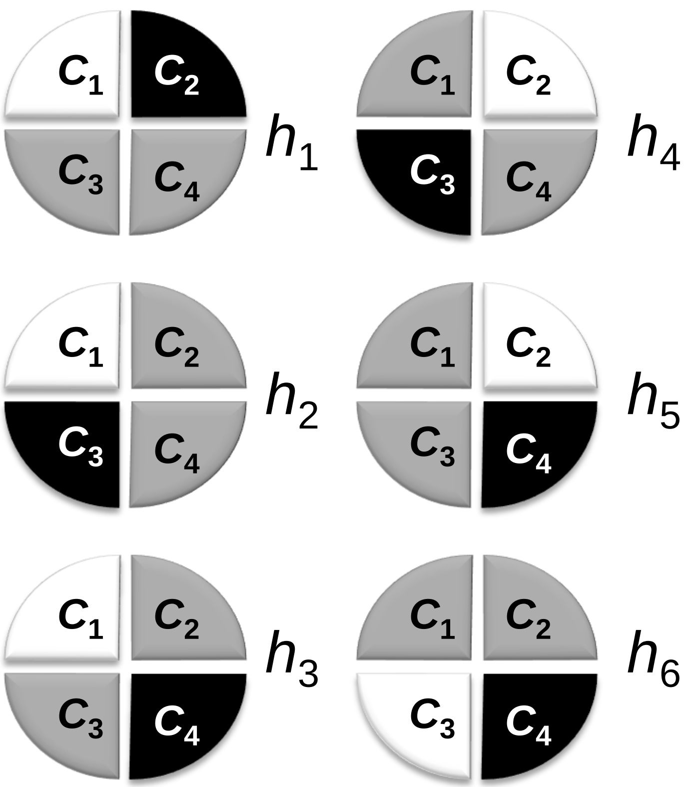




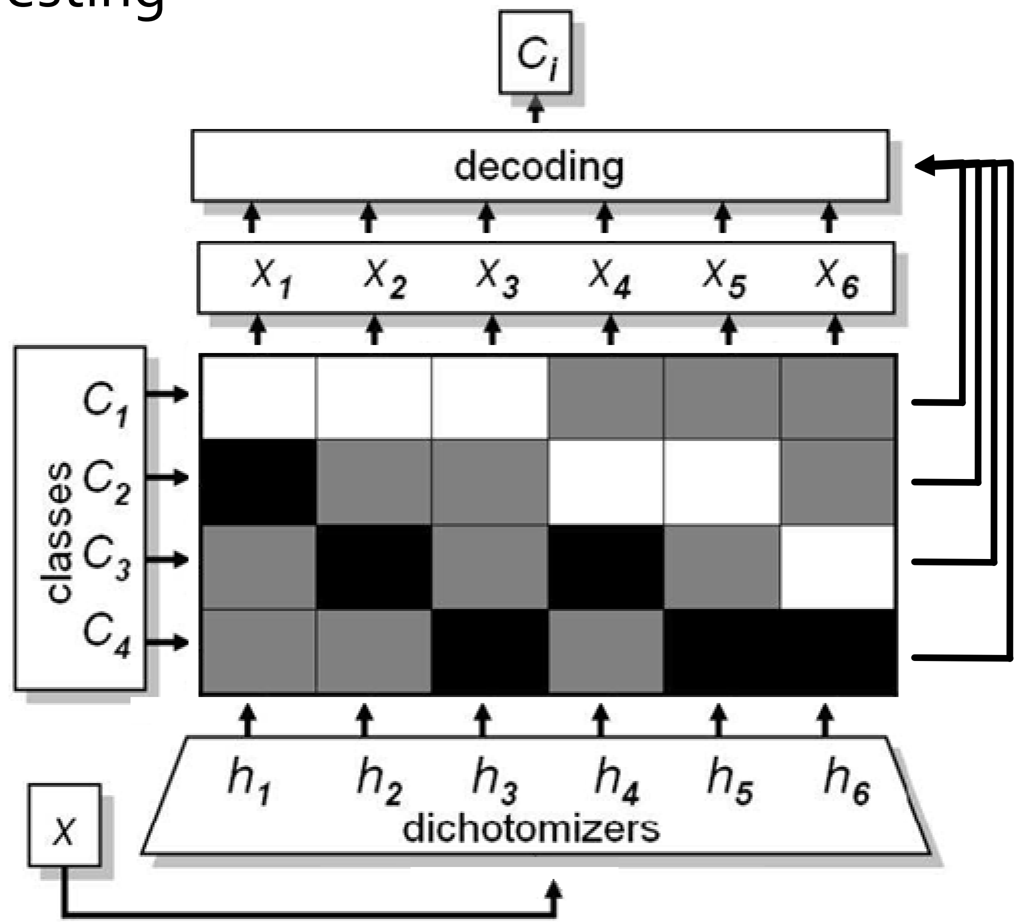
Error-Correcting Output Codes - **Decoding**

Testing

one-versus-one

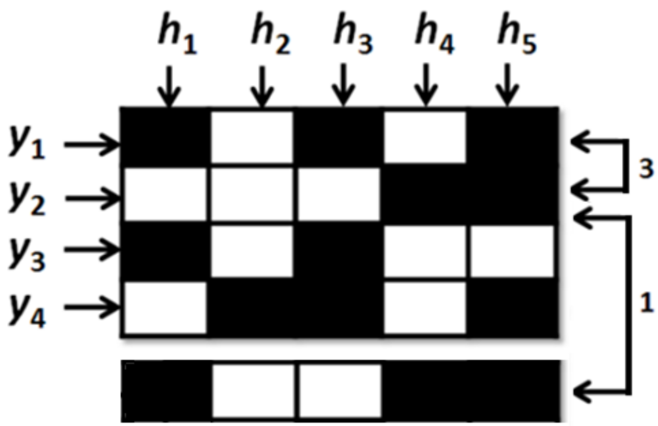


=1 = -1 = 0



Error-Correcting Output Codes

- Properties
  - The information among dichotomizers is used jointly to make a classification decision
  - If the minimum distance among codewords is *d*, then, *(d-1)/2* errors can be corrected at the decoding step **[Dietterich95]**
  - ECOC method reduces the bias and the variance of the learning algorithm **[Kong95]**

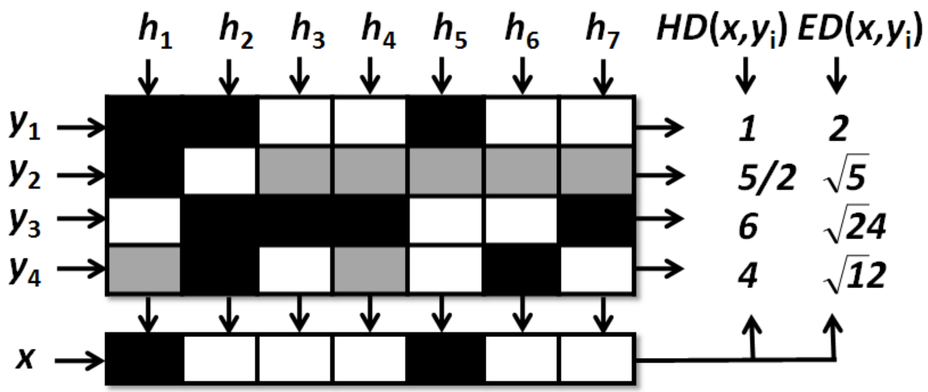


[Dietterich95] Thomas G. Dietterich, Ghulum Bakiri, Solving Multiclass Learning Problems via Error-Correcting Output Codes, Journal of Artificial Intelligence Research, 1995.

[Kong95] E.B. Kong and T.G. Dietterich, Error-Correcting Output Coding Corrects Bias and Variance, Proc. 12th Int'l Conf. Machine Learning, pp. 313-321, 1995.

ECOC - Shortcomings

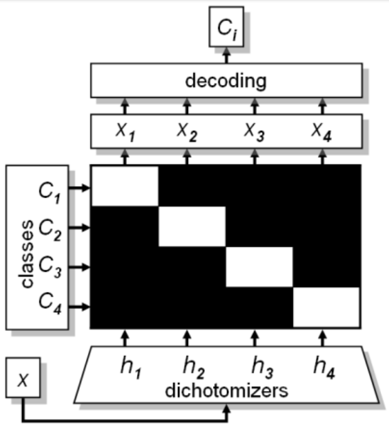
- **ECOC Coding:**
  - Pre-defined ECOC designs
    - Do not use the knowledge of the problem-domain
- **ECOC Decoding:**
  - Ternary ECOC framework **[Allwein02]**
    - Decoding strategies should be readjusted



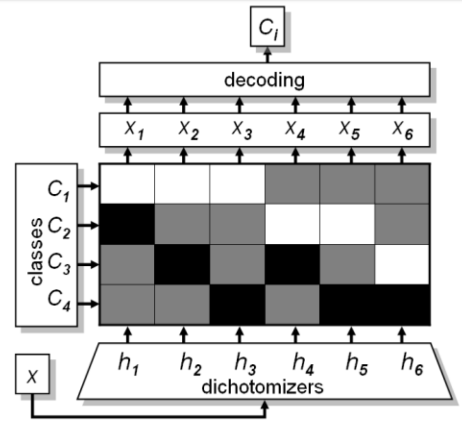
[Allwein02] E. Allwein, R. Schapire, and Y. Singer, Reducing multiclass to binary: A unifying approach for margin classifiers, Journal of Machine Learning Research, vol. 1, pp. 113-141, 2002.

ECOC coding – Classical strategies

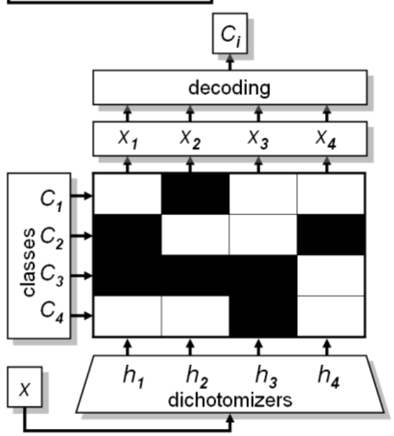
one-versus-all [Nilsson65]



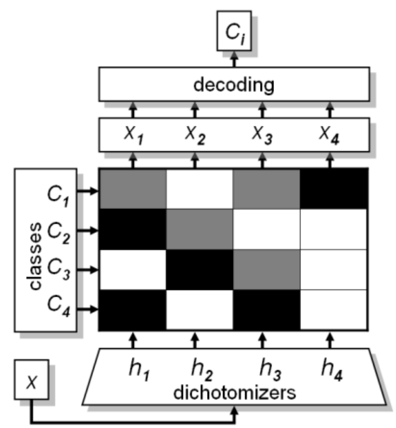
one-versus-one [Hastie98]



dense random [Allwein02]



sparse random [Allwein02]

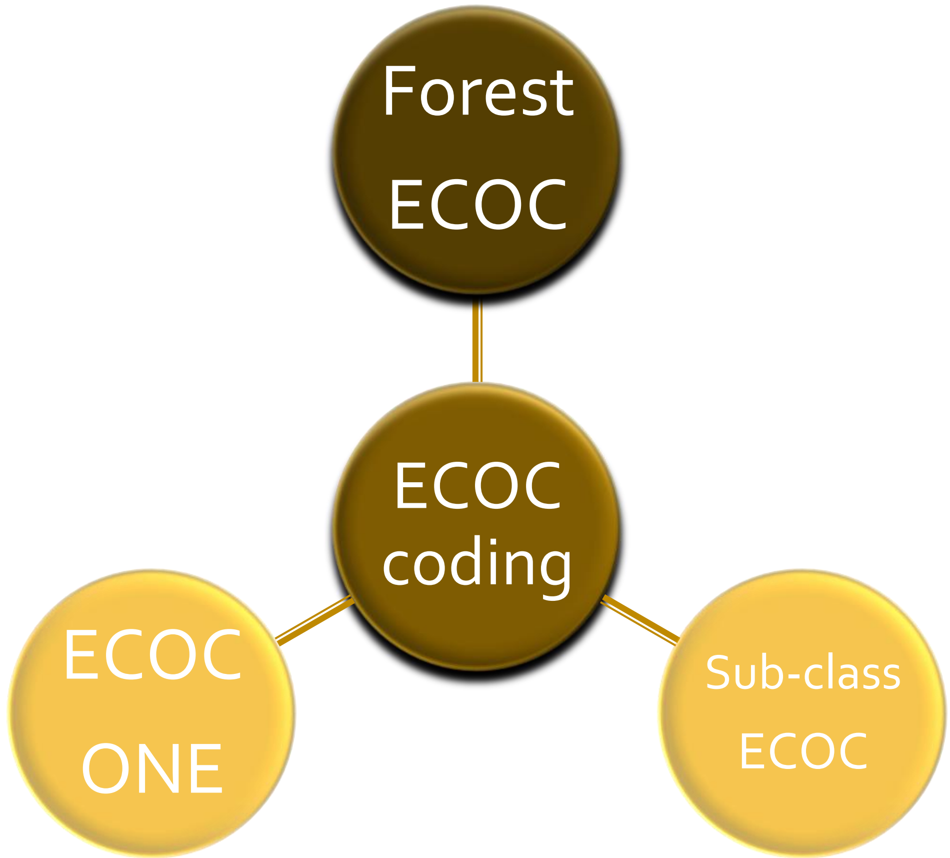


[Hastie98] T. Hastie, R. Tibshirani, Classification by pairwise grouping, The annals of statistics, vol. 26, issue 5, pp. 451–471, 1998.

[Nilsson65] N. J. Nilsson, Learning Machines, McGraw-Hill, 1965.

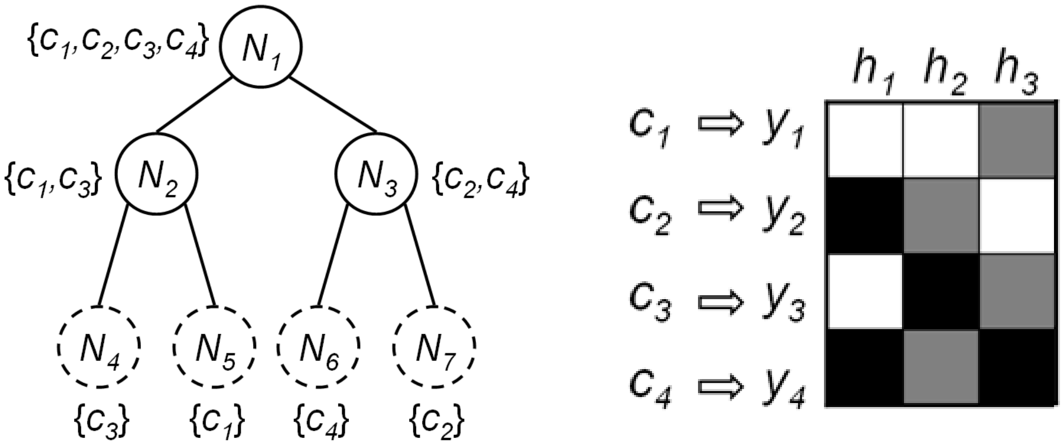
[Allwein02] E. Allwein, R. Schapire, and Y. Singer, Reducing multiclass to binary: A unifying approach for margin classifiers, Journal of Machine Learning Research, vol. 1, pp. 113-141, 2002.

ECOC coding – Our proposal



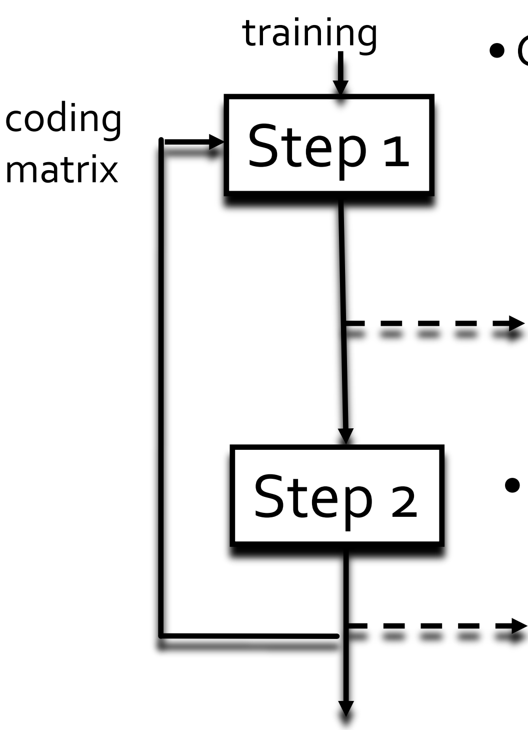
Forest-ECOC

- **Motivation**
  - Use the knowledge of the problem-domain to design the ECOC matrix
  - Take advantage of the embedding of a tree structure in the ECOC matrix to embed a Forest of trees **[Pujol06]**

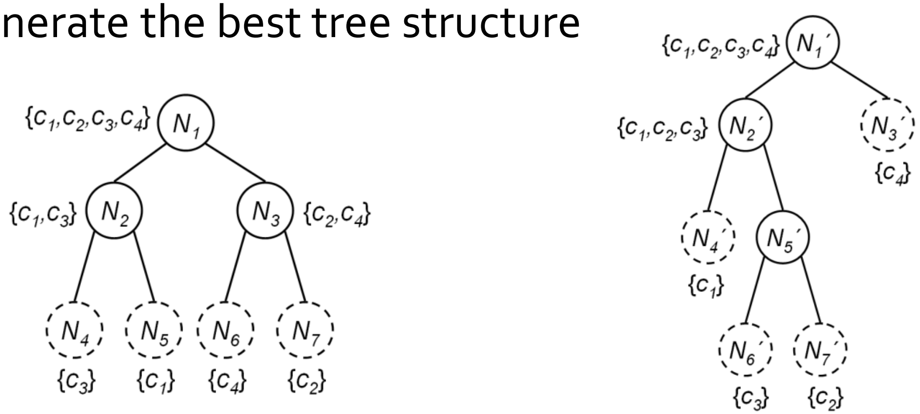


[PujolO6] O. Pujol, P. Radeva, J. Vitrià, Discriminant ecoc: A heuristic method for application dependent design of error correcting output codes, Transactions on PAMI 28 (6) , pp. 1001–1007, 2006.

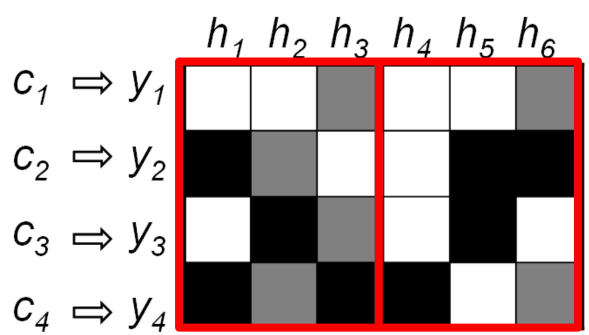
Forest-ECOC



- Generate the best tree structure

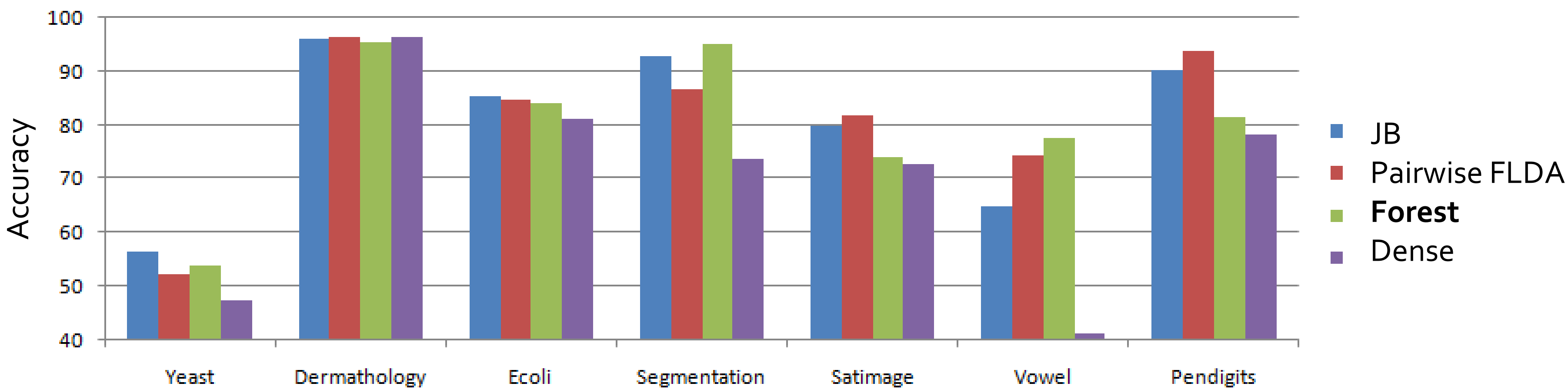


- Embed each internal node of the tree as a new dichotomizer



Forest-ECOC

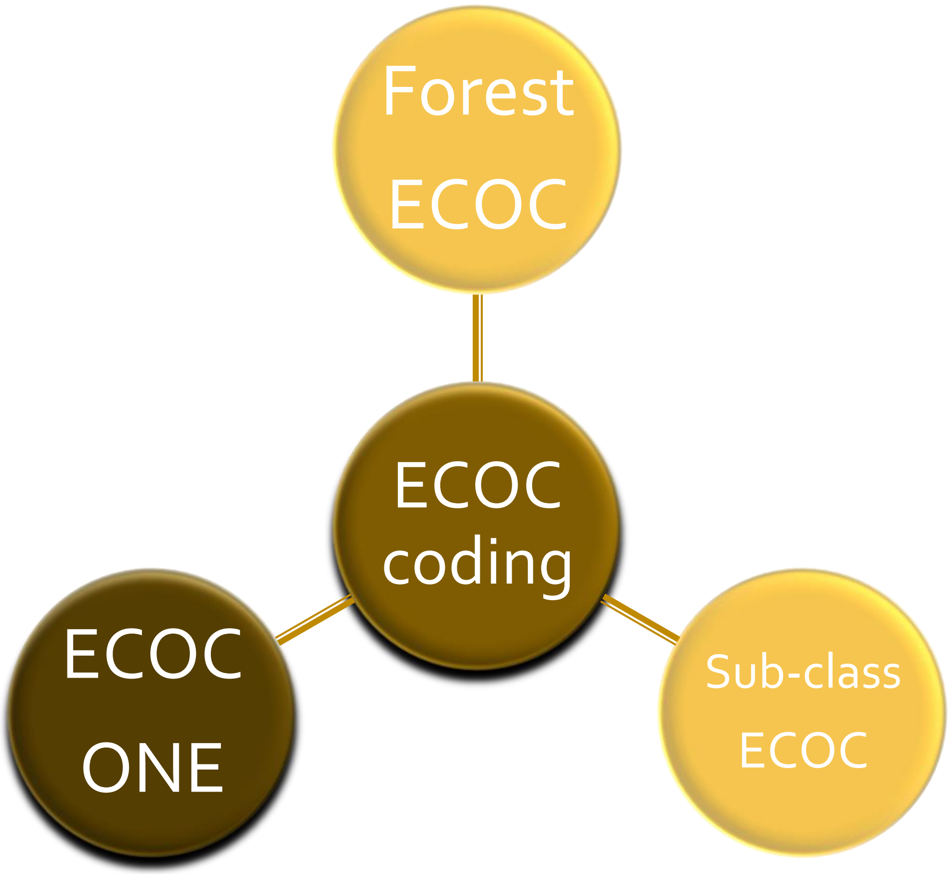
- UCI Machine Learning Repository classification



UCI	JB	all pairs FLDA	Forest ECOC	Dense ramdom ECOC
Rank	1.57	1.57	**1.42**	3.0

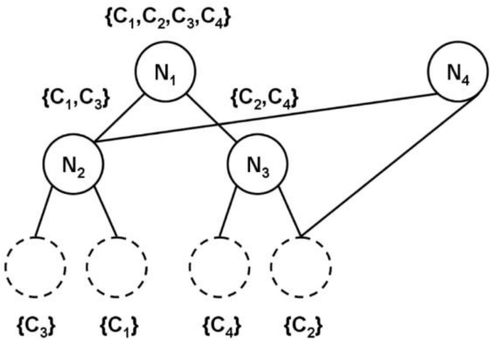
- Small codewords
- Information of tree nodes is shared among classes in the ECOC matrix

ECOC coding – Our proposal



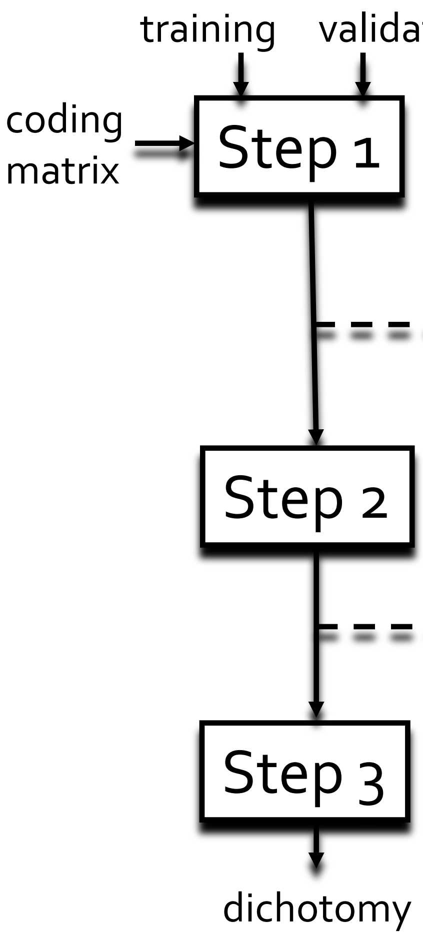
ECOC Optimizing Node Embedding

- Properties
  - Problem-dependent extension of any initial coding (even empty)
    - It focuses on difficult classes
      - It increases the distance between difficult to classify classes while preserving the rest
  - A validation subset is used to increase generalization and prevent or delay overfitting

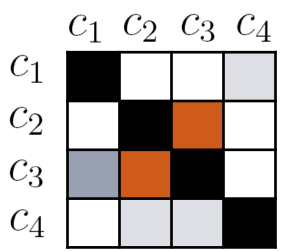


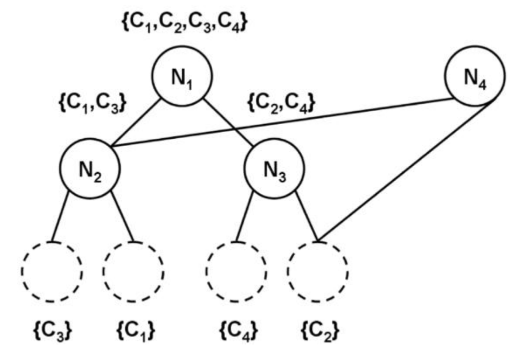
ECOC Optimizing Node Embedding

Coding (Finding a new dichotomy)



- Find the empirical error on the training and validation subsets





- Select the pair of classes with highest error from the joint confusion matrix

$\{C_2,\ldots\}$ vs $\{C_3,\ldots\}$

	h_1	h_2	h_3	h_4
C_1	1	-1	0	1
C_2	-1	0	-1	-1
C_3	1	1	0	1
C_4	-1	0	1	0

- Complete the sets of classes minimizing the joint error

(Sequential Forward Floating Search strategy)

ECOC Optimizing Node Embedding

Coding (Embedding)

dichotomy {C2} vs {C3, C1}

Embedding

- Embed the new dichotomy in the matrix

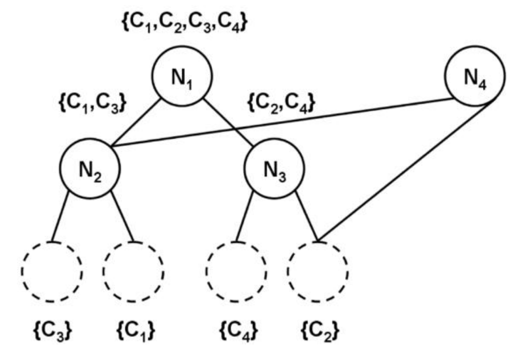
$$M(r,i) = \begin{cases} 0 & if \quad c_r \notin C_i \\ +1 & if \quad c_r \in C_{i1} \\ -1 & if \quad c_r \in C_{i2} \end{cases}$$

Weighting

- Update the dichotomy importance

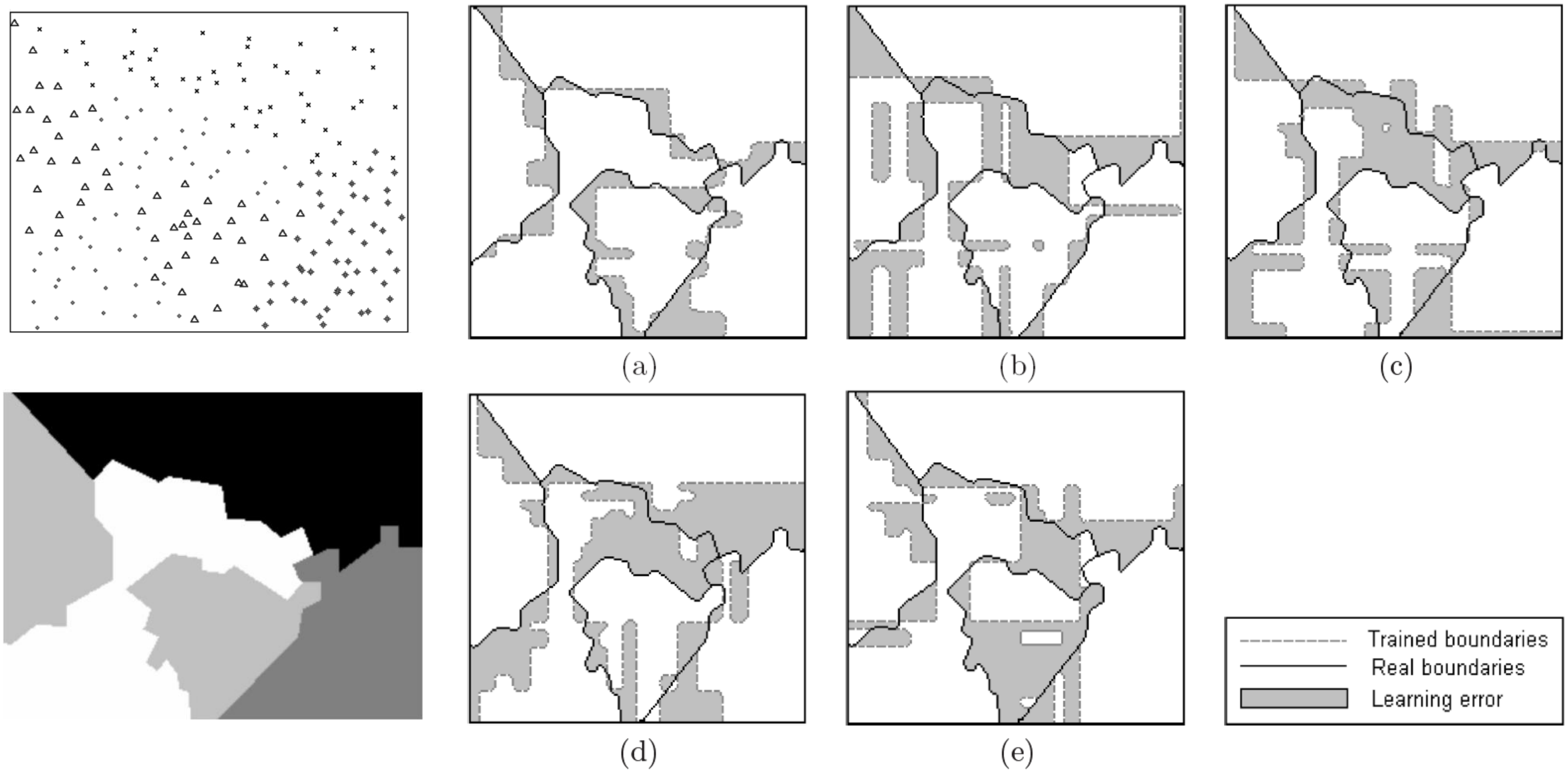
$$w_i = 0.5 \log\left(\frac{1-e_i}{e_i}\right)$$

1.0	weights
original code	extended code



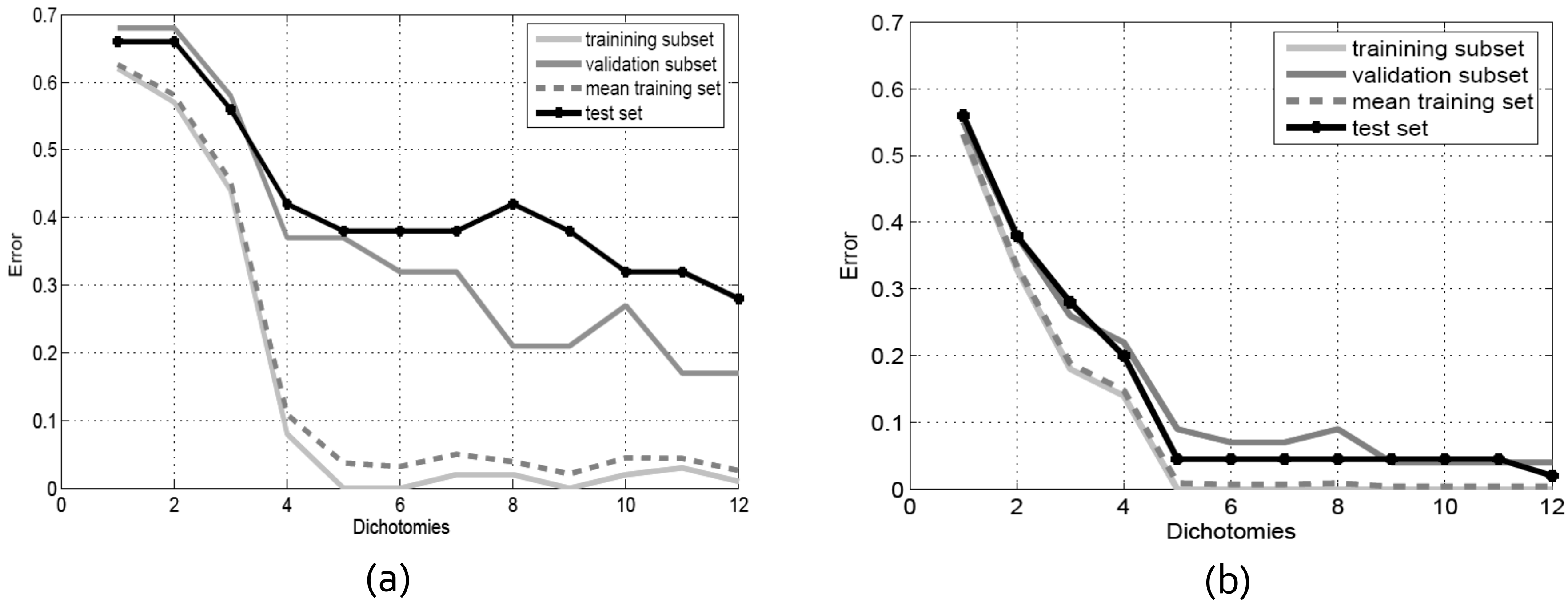
	h_1	h_2	h_3	h_4
C_1	1	-1	0	1
C_2	-1	0	-1	-1
C_3	1	1	0	1
C_4	-1	0	1	0

ECOC Optimizing Node Embedding



Boundaries resulted after one iteration of training. (a) ECOC-ONE, (b) one-versus-one, (c) one-versus-all and, (d) and (e) two different matrices of Dense Random with the same minimal distance, respectively. Dark line corresponds to the real boundary and grey regions correspond to learning errors.

ECOC Optimizing Node Embedding

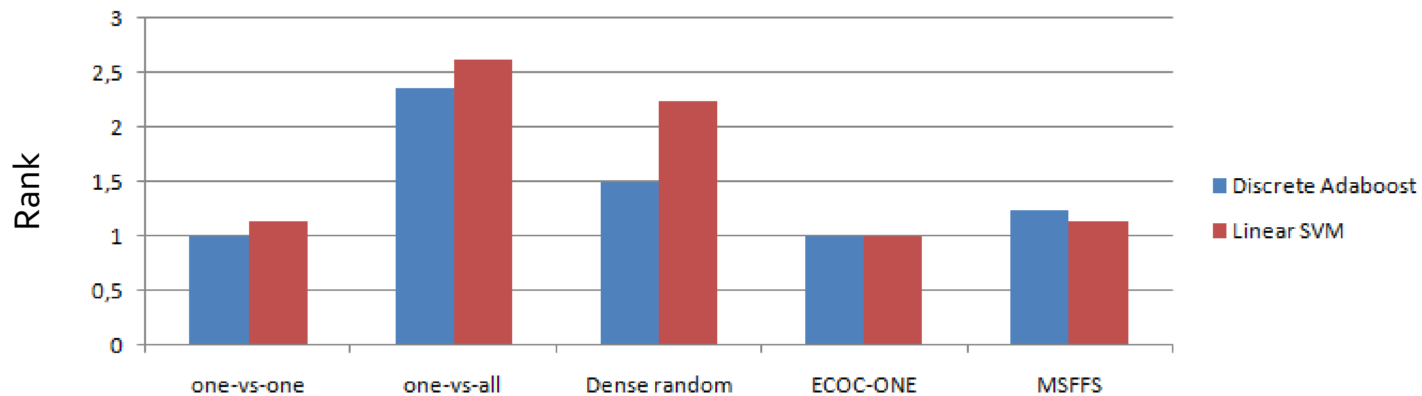


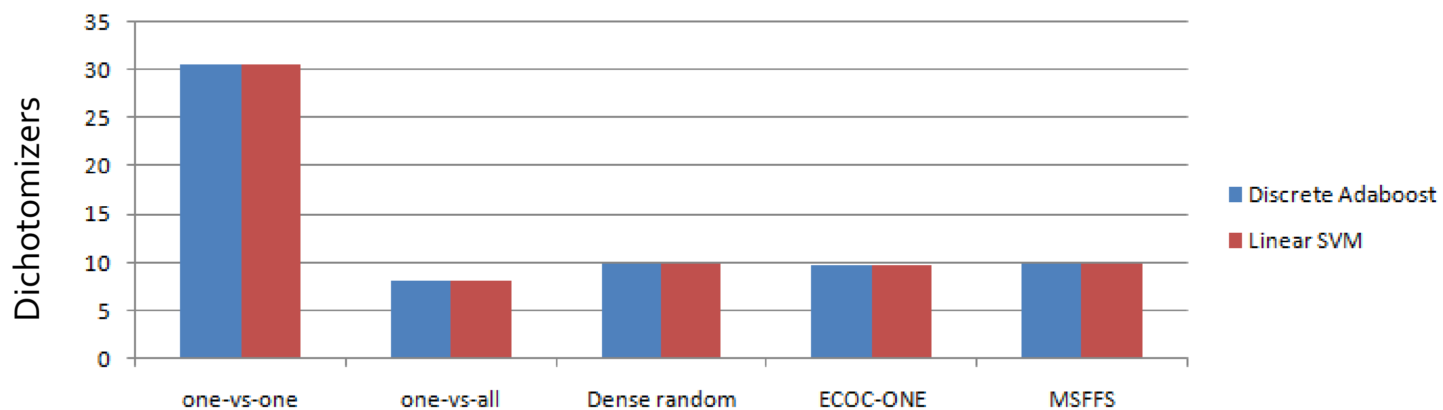
Error evolution using ECOC-ONE with FLDA for:

(a) **Glass** data set

(b) **Dermathology** data set

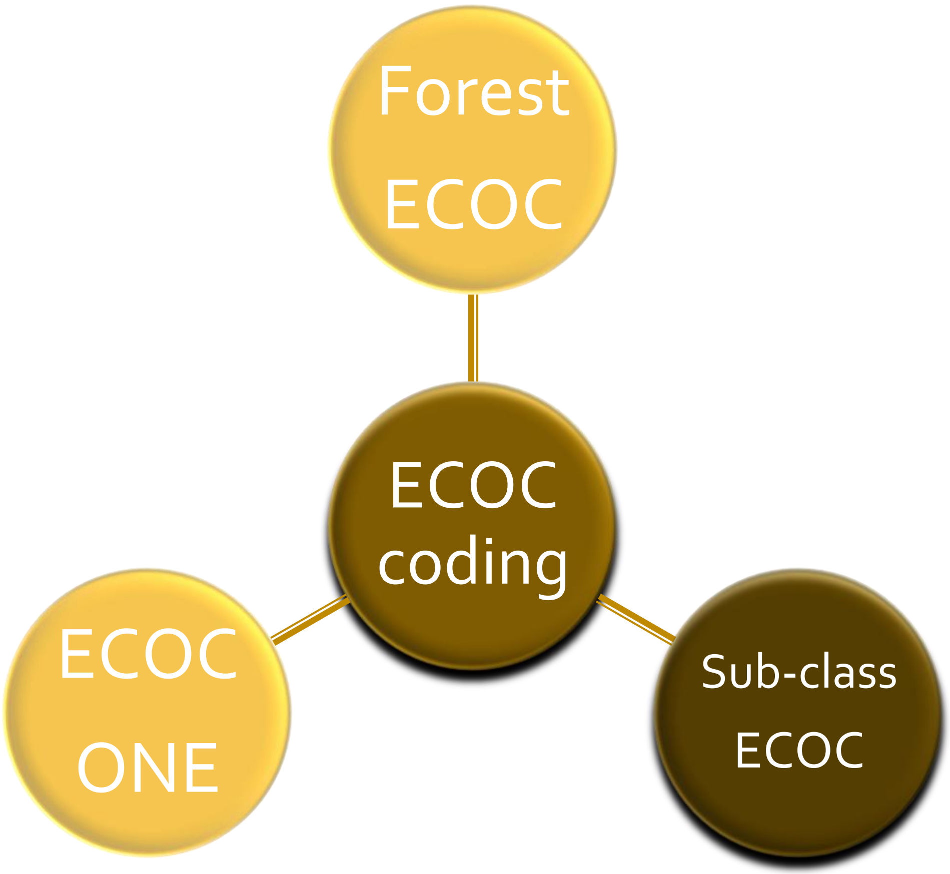
ECOC Optimizing Node Embedding





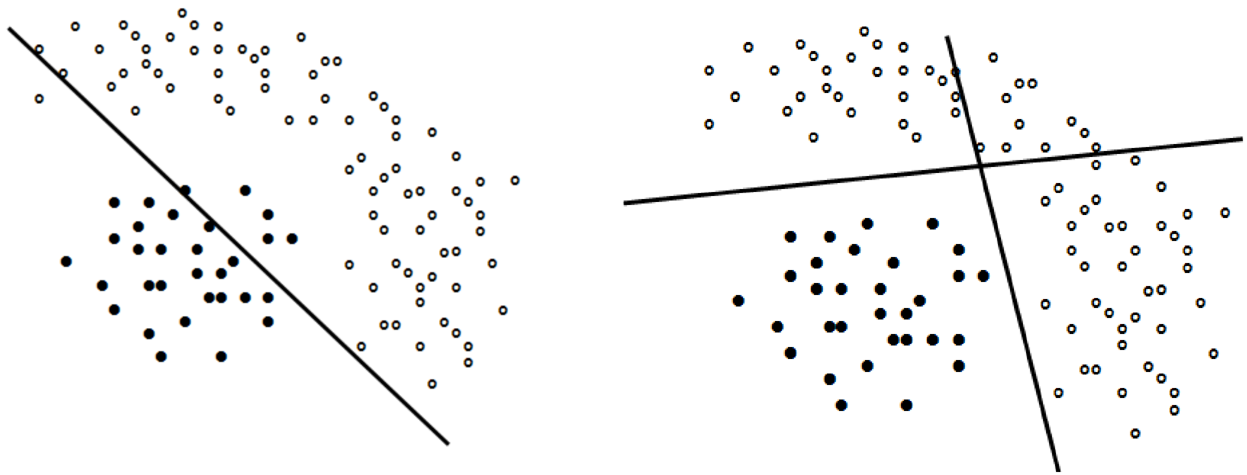
- The length of the codeword is increased in the way that a better solution for the training data is obtained
- It can be applied to any initial coding matrix, yielding a small code length

ECOC coding – Our proposal

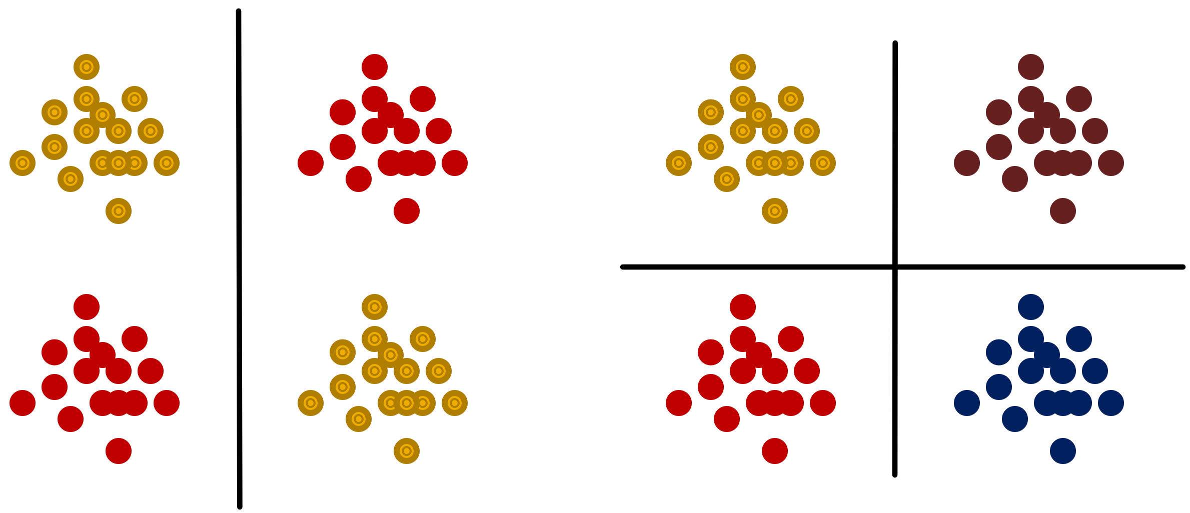


Sub-class ECOC

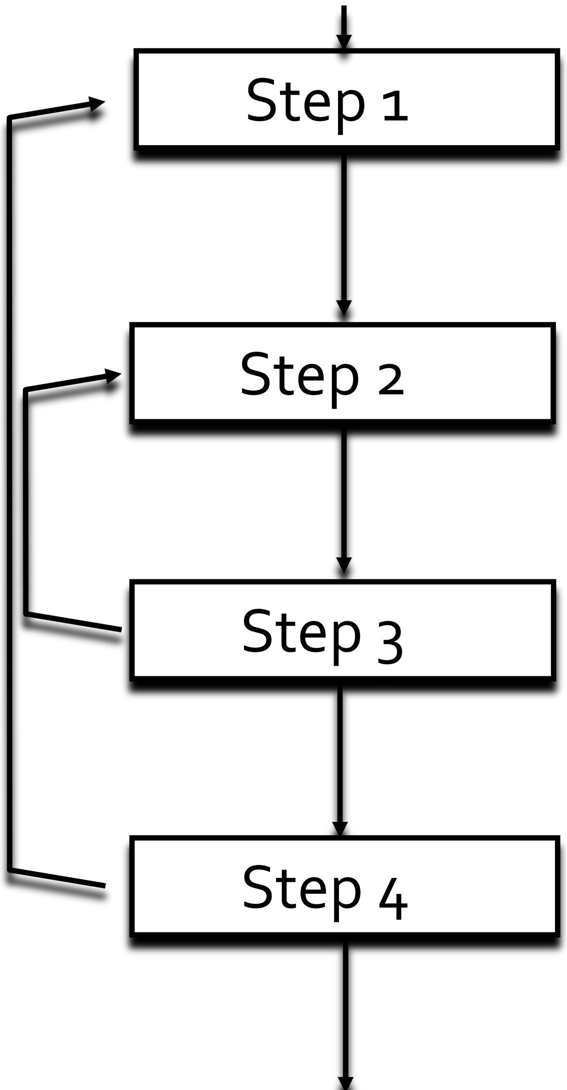
- Linear classifier



- Adaboost



Sub-class ECOC



- Find the next optimal tree node based on SFFS and Mutual Information
- Test the node performance using a base classifier
- If training error > epsilon:
  - Split the node data into subclasses maximizing inter-class cluster distance
- Embed the new dichotomizers

	h_1
C_1	1
C_2	1
C_3	-1

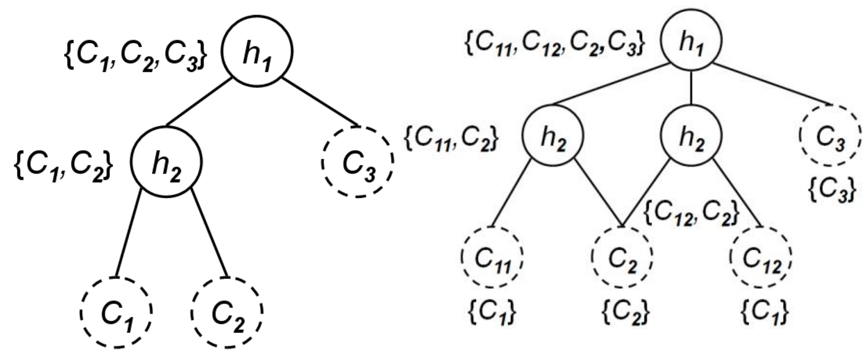
(a)

	h_1	h_2
C_1	1	1
C_2	1	-1
C_3	-1	0

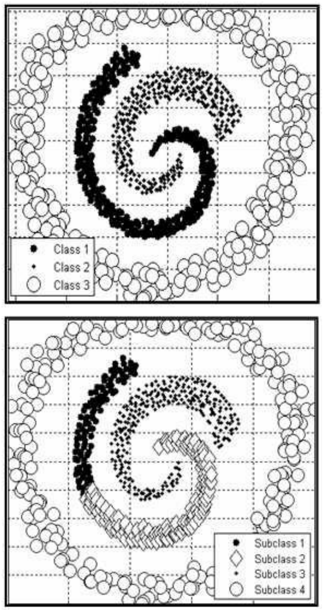
(b)

	h_1	h_2	h_3
C_{11}	1	1	0
C_{12}	1	0	1
C_2	1	-1	-1
C_3	-1	0	0

(c)



Sub-class ECOC



Sub-class learning example

	h_1
c_1	1
c_2	1
c_3	-1

(a)

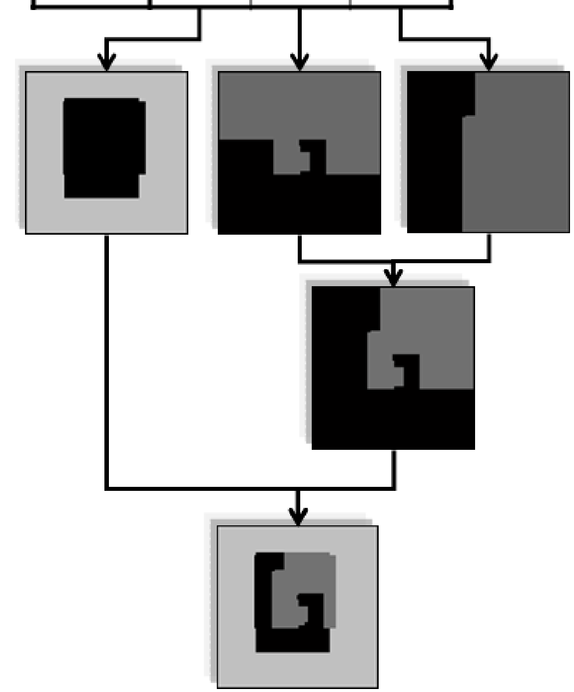
	h_1	h_2
c_1	1	1
c_2	1	-1
c_3	-1	0

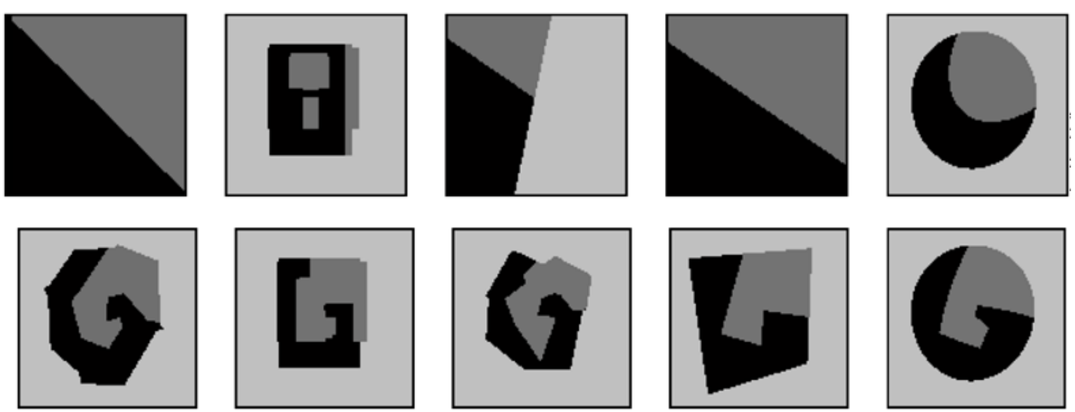
(b)

	h_1	h_2	h_3
c_{11}	1	1	0
c_{12}	1	0	1
c_2	1	-1	-1
c_3	-1	0	0

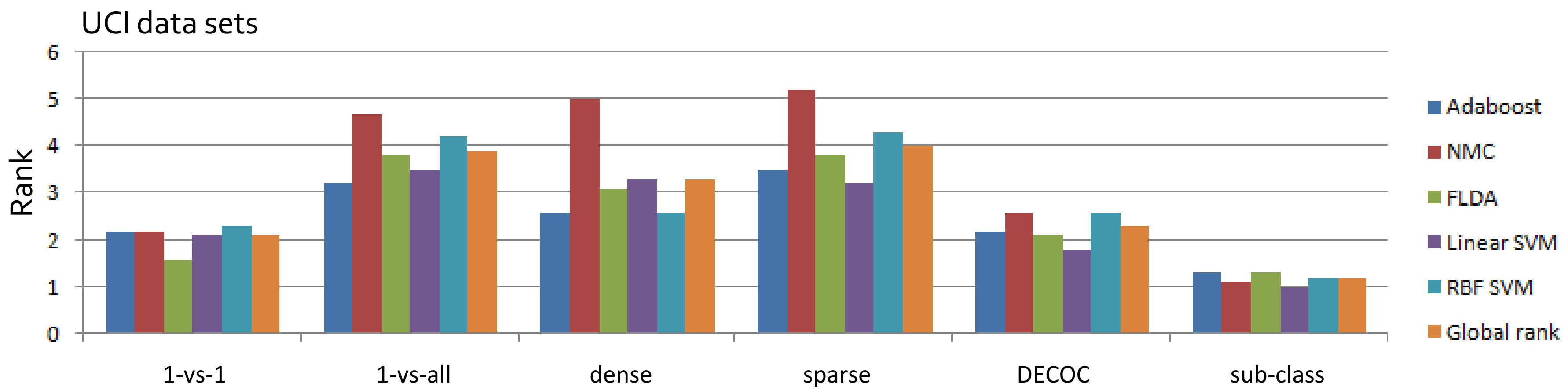
(c)

	h_1	h_2	h_3
c_{11}	1	1	0
c_{12}	1	0	1
c_2	1	-1	-1
c_3	-1	0	0

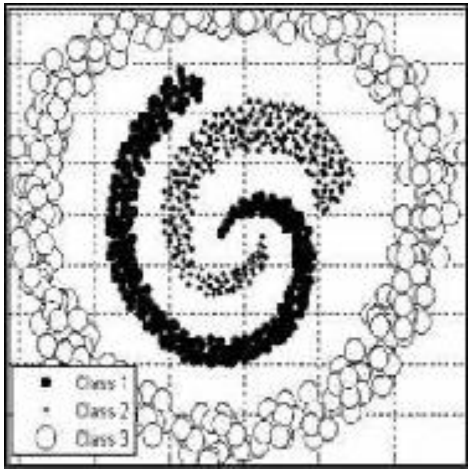




Sub-class ECOC

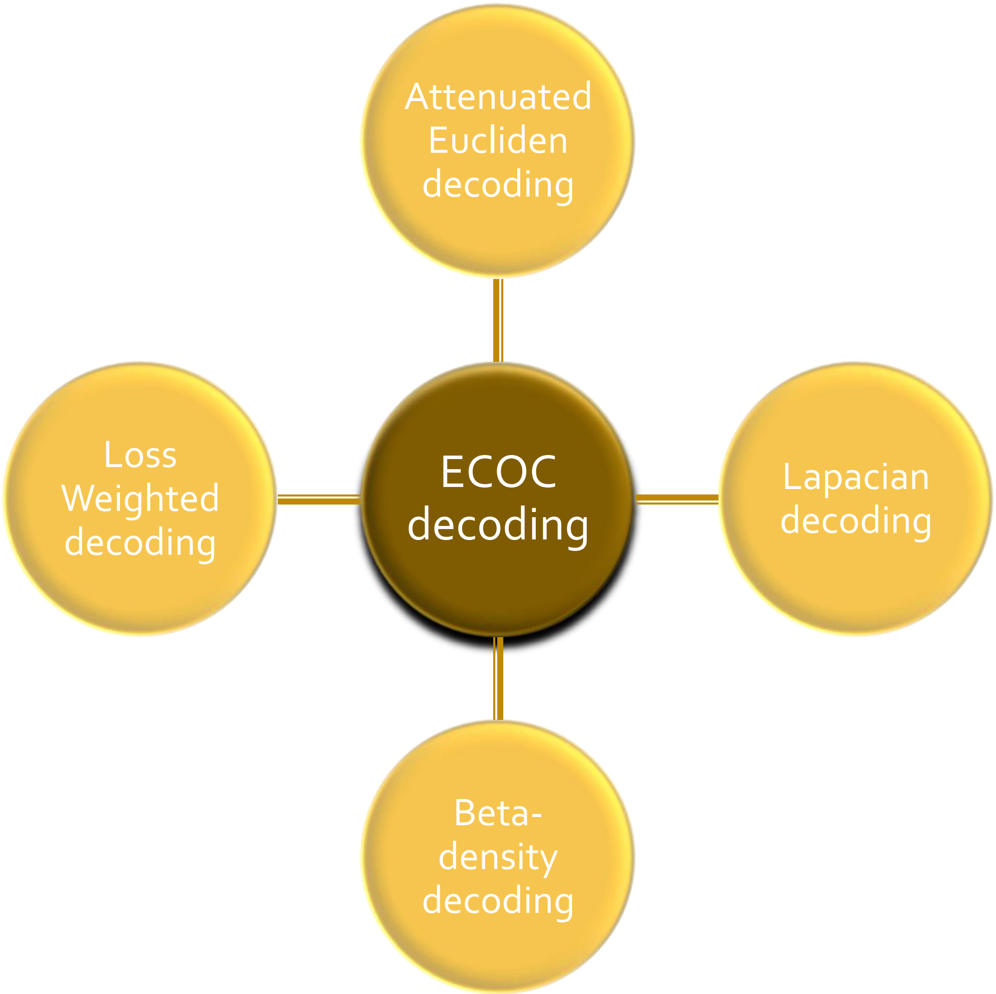


Learning boundaries evolution



- Sub-class ECOC splits the original set of classes into sub-classes until the base classifier is able to learn the training data
- Useful when ECOC base classifier is not able to model the binary problems
- It avoids the requirement of using complex classifiers

ECOC decoding – Our proposal



ECOC decoding – Classical strategies

Hamming decoding **[Nilsson65]**

$$HD(x,y_i) = \sum_{j=1}^{n}(1-\text{sign}(x^j \cdot y_i^j))/2$$

Inverse Hamming decoding **[Windeatt03]**

$$IHD(x,y_i) = \max(\Delta^{-1}D^T),\ \Delta(i_1,i_2) = HD(y_{i_1},y_{i_2})$$

Euclidean decoding **[Hastie98]**

$$ED(x,y_i) = \sqrt{\sum_{j=1}^{n}(x^j - y_i^j)^2}$$

Loss-based decoding **[Allwein02]**

$$LB(\rho,y_i) = \sum_{j=1}^{n} L(y_i^j \cdot f^j(\rho)) \qquad L(\theta) = -\theta\ ,\ L(\theta) = \mathbf{e}^{-\theta}$$

Probabilistic-based decoding **[Passerini04]**

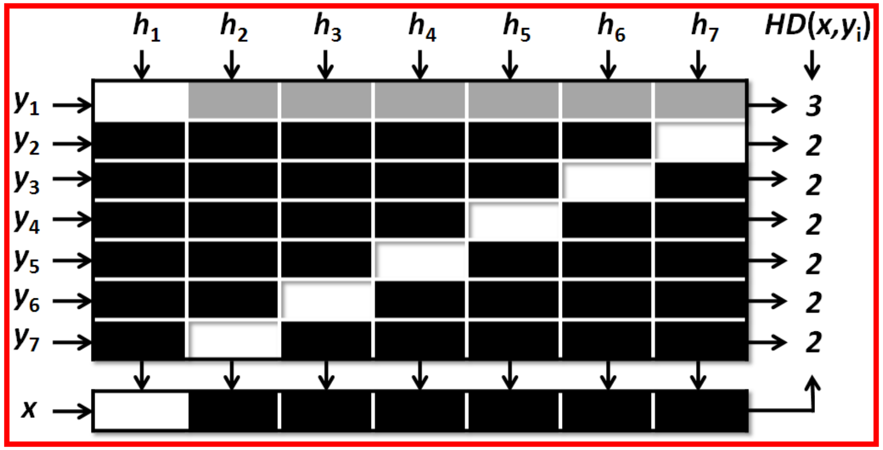
$$PD(y_i,F) = -log\left(\prod_{j\in[1,\ldots,n]:M(i,j)\neq 0} P(x^j = M(i,j)|f^j) + K\right)$$

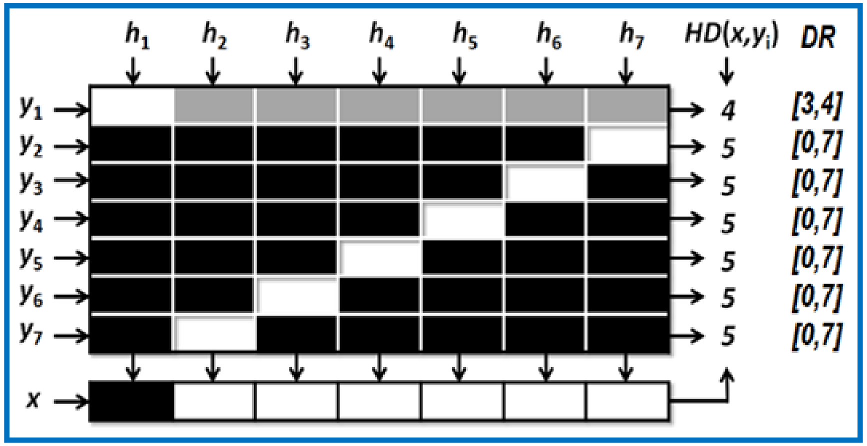
$$P(x^j = y_i^j|f^j) = \frac{1}{1+\mathbf{e}^{y_i^j(\upsilon^j f^j + \omega^j)}}$$

[Nilsson65] N. J. Nilsson, "Learning Machines", McGraw-Hill, 1965.
[Windeatt03] T. Windeatt and R. Ghaderi, "Coding and decoding for multi-class learning problems", Information Fusion, vol. 4, pp. 11-21, 2003.
[Hastie98] T.Hastie and R.Tibshirani, "Classification by pairwise grouping", In proc. NIPS , vol. 26, pp. 451-471, 1998.
[Allwein02] E. Allwein, R. Schapire, and Y. Singer, Reducing multiclass to binary: A unifying approach for margin classifiers, Journal of Machine Learning Research, vol. 1, pp. 113-141, 2002.
[Passerini04] A. Passerini, M. Pontil, and P. Frasconi, "New results on error correcting output codes of kernel machines", IEEE Transactions on Neural Networks, vol. 15(1), pp. 45-54, 2004.

Taxonomy

$$HD(x, y_i) = \sum_{j=1}^{n} (1 - \text{sign}(x^j \cdot y_i^j))/2$$





Definition 1: ***Decoding bias*** *is the value introduced by the comparison of two codewords on positions containing the zero symbol (being the magnitude of the value proportional to the number of zero positions).*

Definition 2: ***A dynamic range bias*** *corresponds to the difference among the ranges of values associated to the decoding process of each codeword.*

Taxonomy

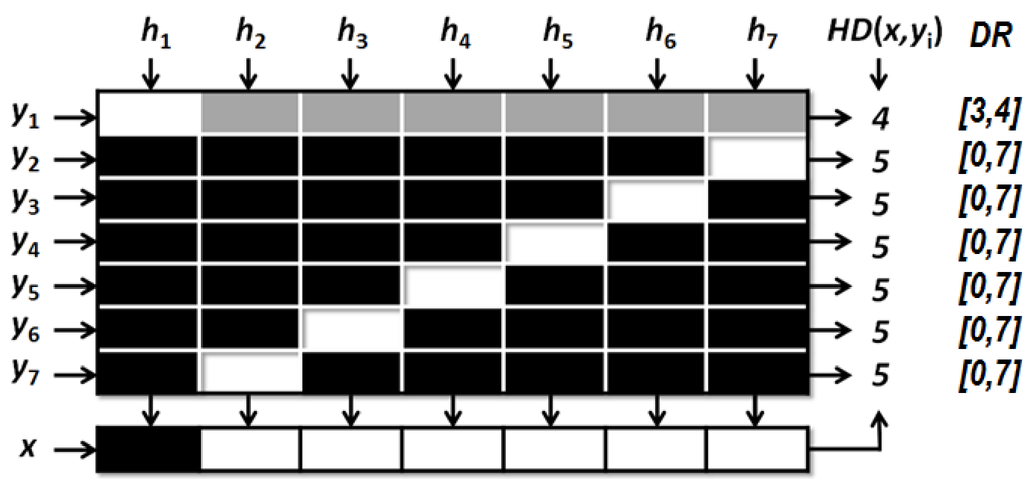
***Definition 3**: A general decoding decomposition to represent decoding strategies is defined as follows:*

$$d = \sum_{k \in I_b} b_k + \sum_{i \in I_a} a_i + \sum_{j \in I_e} e_j$$

b – Value of a zero comparison
a – Value of a maching
e – Value of a failure
I_b, I_a, I_e - Index

***Hypothesis I**: The bias induced by a zero position applying a particular decoding strategy should be zero (b=0)*

***Hypothesis II**: The dynamic range should be constant for all the codewords*



Taxonomy

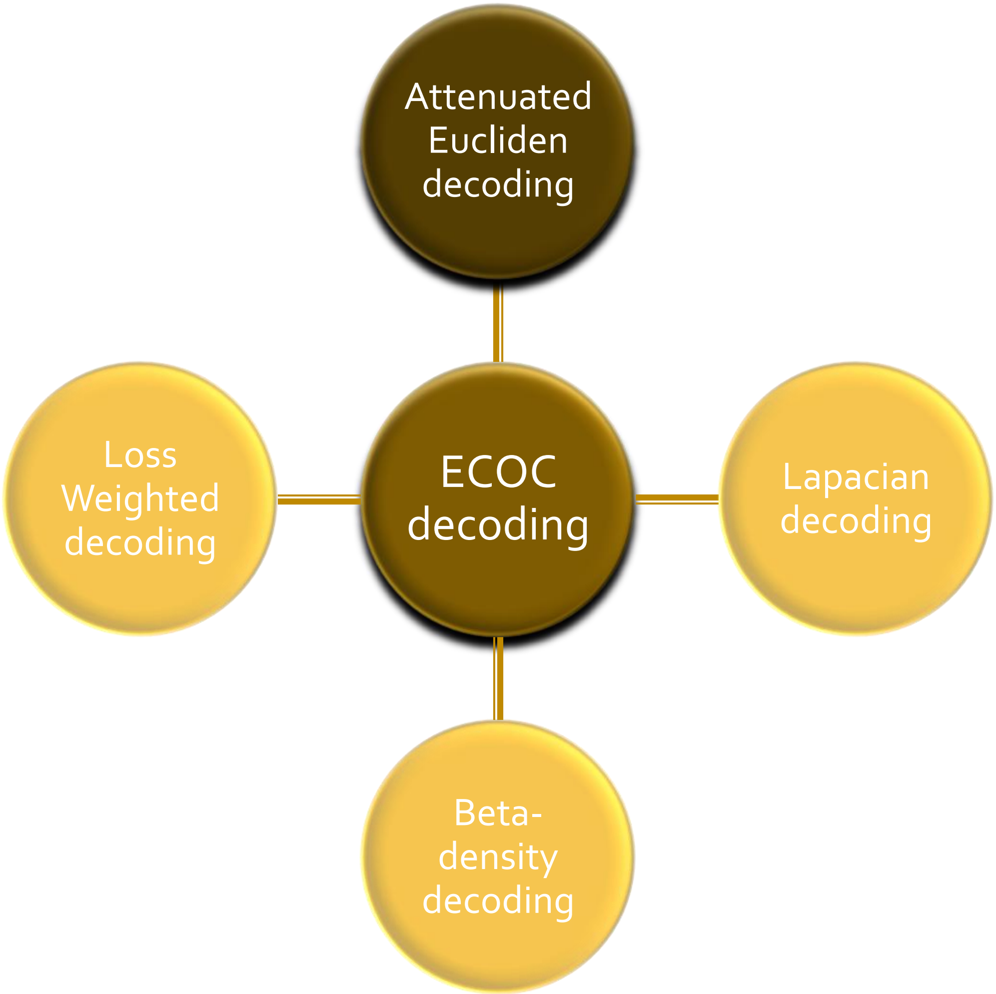
	$b \neq 0$	$b = 0$
Different *dynamic ranges*	Type 0	Type I
Same *dynamic ranges*	Type II	Type III

$$d = \sum_{k \in I_b} b_k + \sum_{i \in I_a} a_i + \sum_{j \in I_e} e_j$$

b – value of a zero comparison, a – value of a maching, e – value of a failure

Strategy	b	a	e	
HD	1/2	0	1	Type 0
IHD	$\frac{-1}{2}\ W_1 + \sum_{i=2}^{N} \frac{W_i z_i}{z_1}$	0	$-1\ W_1 + \sum_{i=2}^{N} \frac{W_i \beta_i}{\beta_1}$	Type 0
ED	1	0	4	Type 0
LLB_C	0	$-\lvert f(\rho)\rvert$	$\lvert f(\rho)\rvert$	Type I
LLB_D	0	-1	1	Type I
ELB_C	1	$1/\mathbf{e}^{\lvert f(\rho)\rvert}$	$\mathbf{e}^{\lvert f(\rho)\rvert}$	Type 0
ELB_D	1	$1/\mathbf{e}$	$\mathbf{e}$	Type 0
PD_C	0	$\log \frac{1}{1+\mathbf{e}^{\lvert f(\rho)\rvert}}$	$\log \frac{1}{1+1/\mathbf{e}^{\lvert f(\rho)\rvert}}$	Type I
PD_D	0	$\log \frac{1}{1+\mathbf{e}}$	$\log \frac{1}{1+1/\mathbf{e}}$	Type I

ECOC decoding – Our proposal

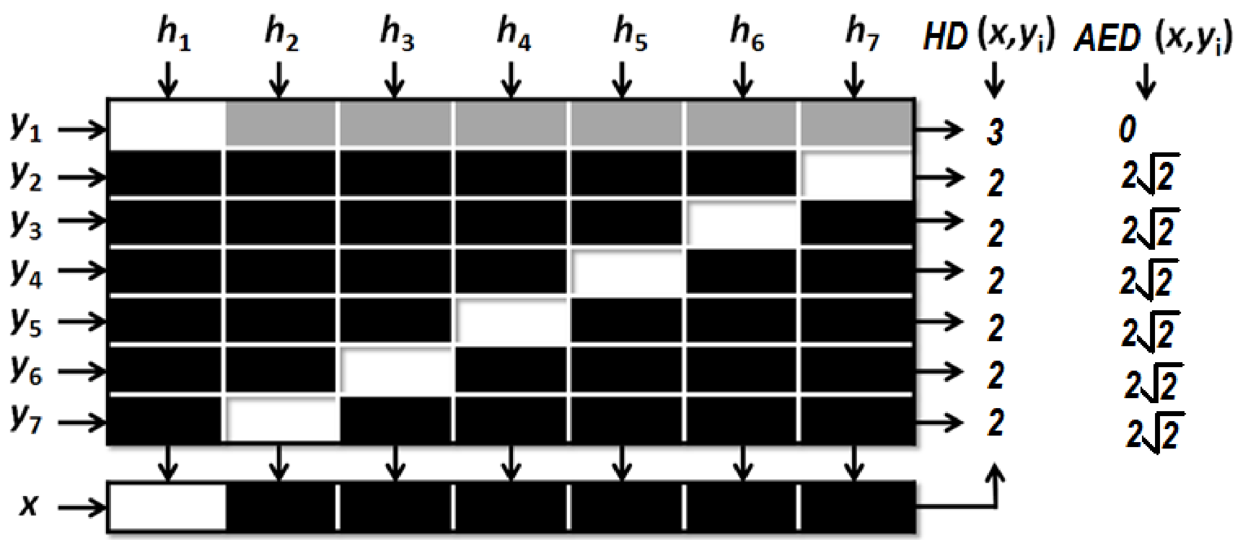


Attenuated Euclidean decoding

- **Motivation**: Avoid the zero bias

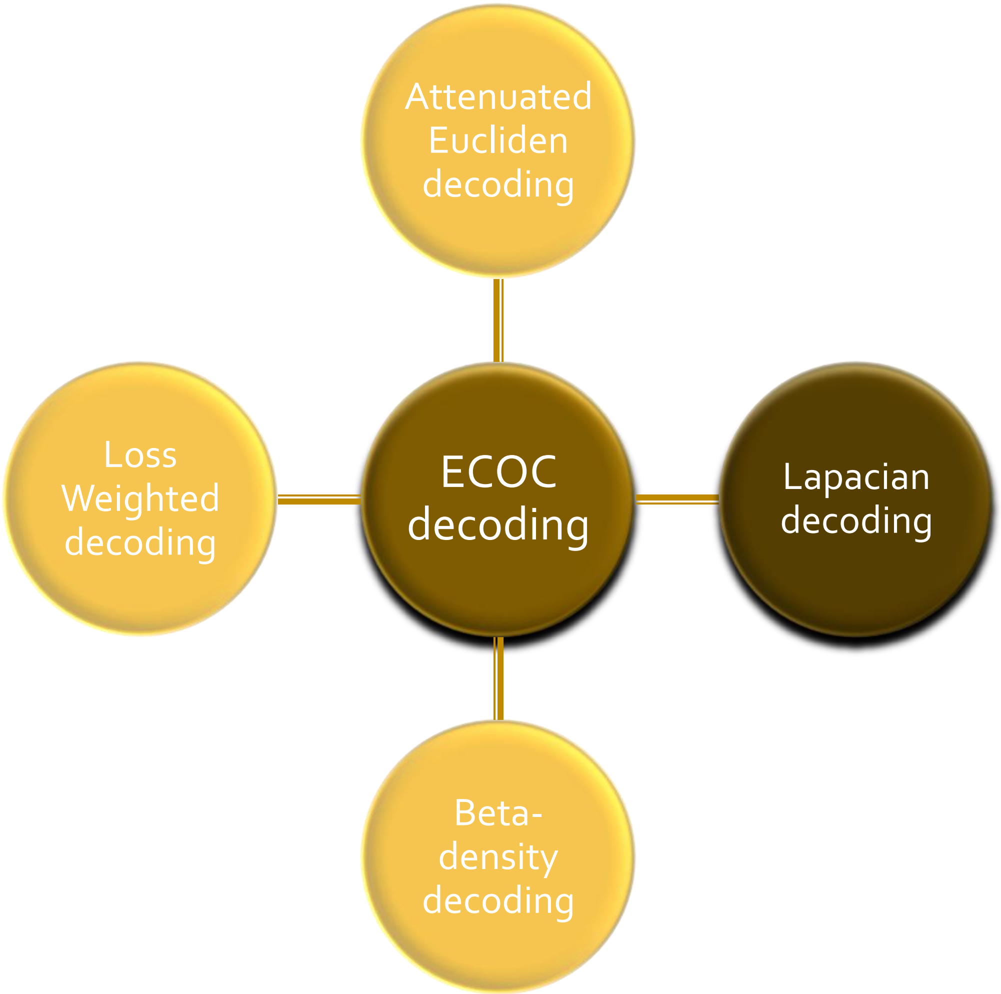
$$AED(x, y_i) = \sqrt{\sum_{j=1}^{n} | y_i^j || x^j | (x^j - y_i^j)^2}$$

$$AED(x, y) = \sum_{j \in I_e} e_j = \sum_{j \in I_e} 4 = 4\beta$$



- Still the dynamic ranges differ

ECOC decoding – Our proposal



Laplacian decoding

- **Motivation**: Avoid the zero bias and make the dynamic ranges comparable

$$d = \sum_{k \in I_b} b_k + \sum_{i \in I_a} a_i + \sum_{j \in I_e} e_j$$

b – Value of a zero comparison
a – Value of a maching
e – Value of a failure
I_b, I_a, I_e - Index

- Define a measure that counts the number of coincidences between the input codeword and the class codeword

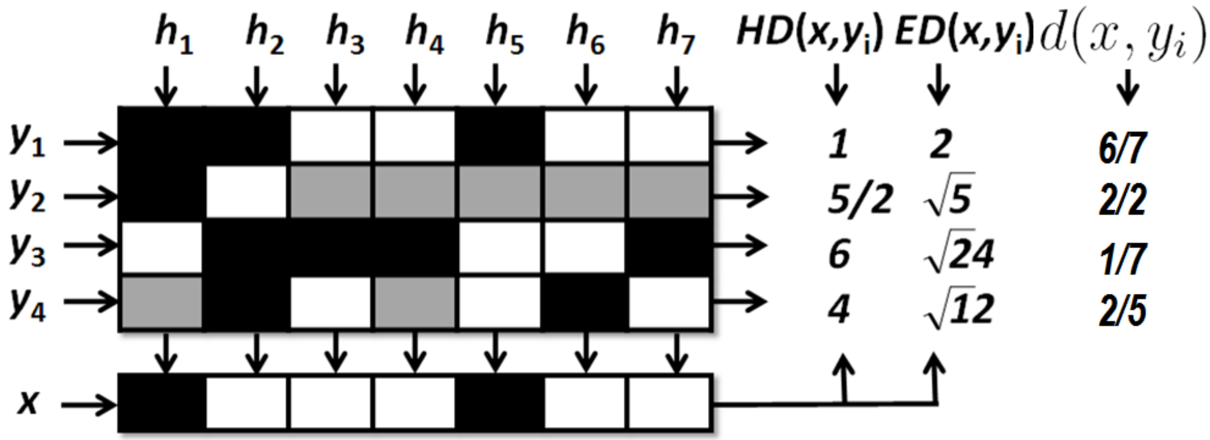
- In order to get constant dynamic ranges, the measure is normalized by the total number of positions coded by {-1,+1}:

$$d(x, y_i) = \frac{\alpha_i}{\alpha_i + \beta_i}$$

Number of matches
Number of failures

Laplacian decoding

$$d(x, y_i) = \frac{\alpha_i}{\alpha_i + \beta_i}$$

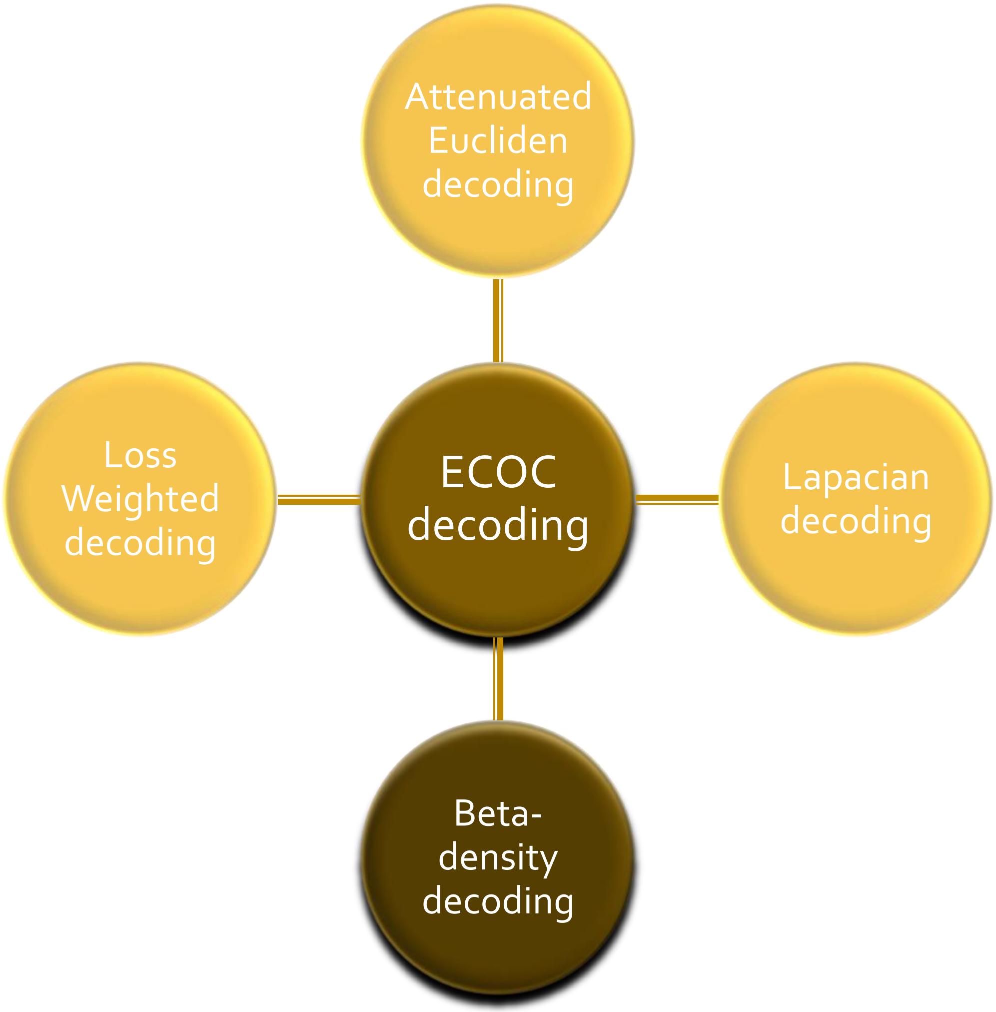


- The main drawback of this definition is that it is not robust when there is a small number of coded positions in one word
- We introduce a prior bias, known as the Laplace Correction:

$$LAP(x, y_i) = \frac{\alpha_i + 1}{\alpha_i + \beta_i + K}$$

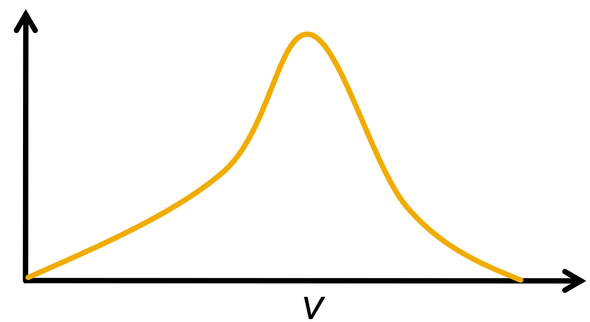
where K is an integer value that codifies the number of classes considered by the classifier – two in this case

ECOC decoding – Our proposal



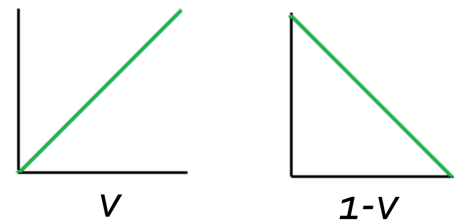
Pessimistic Beta-Density Distribution decoding

- **Motivation**: introduce confidence to the previous Laplacian decoding approximation
  - Based on PDF estimation between two codewords
  - Model the accuracy and uncertainty based on a pessimistic score



  - We use an extension of the continuous binomial distribution, the Beta-distribution:

$$\psi_i(\nu, \alpha_i, \beta_i) = \frac{1}{K}\nu^{\alpha_i}(1-\nu)^{\beta_i}$$

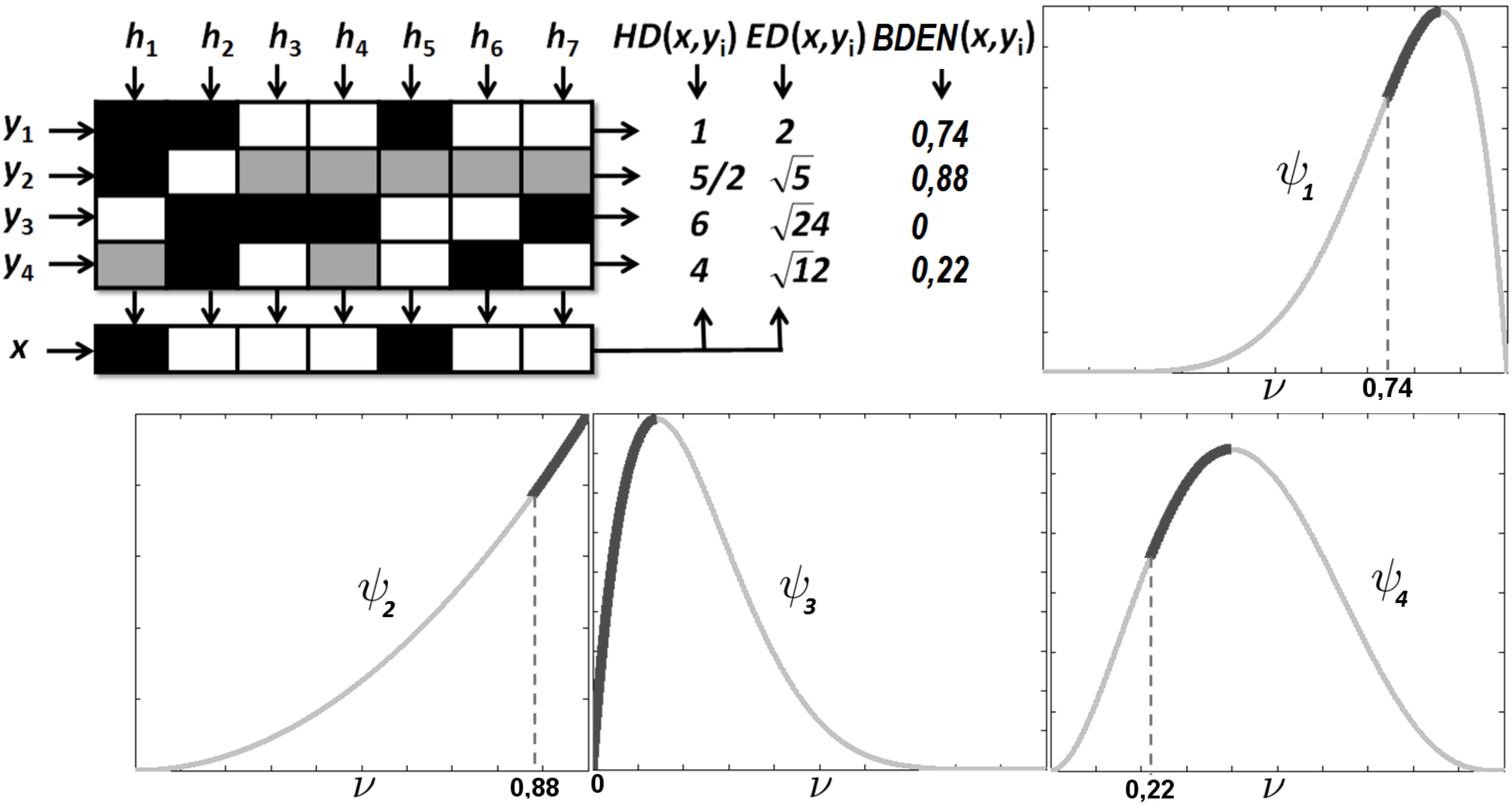


  - The class which achieves the highest score s, defined as the pessimistic score, is assigned to the test codeword:

$$s_i \;:\; \int_{\nu_i - s_i}^{\nu_i} \psi_i(\nu, \alpha_i, \beta_i)d\nu = u$$

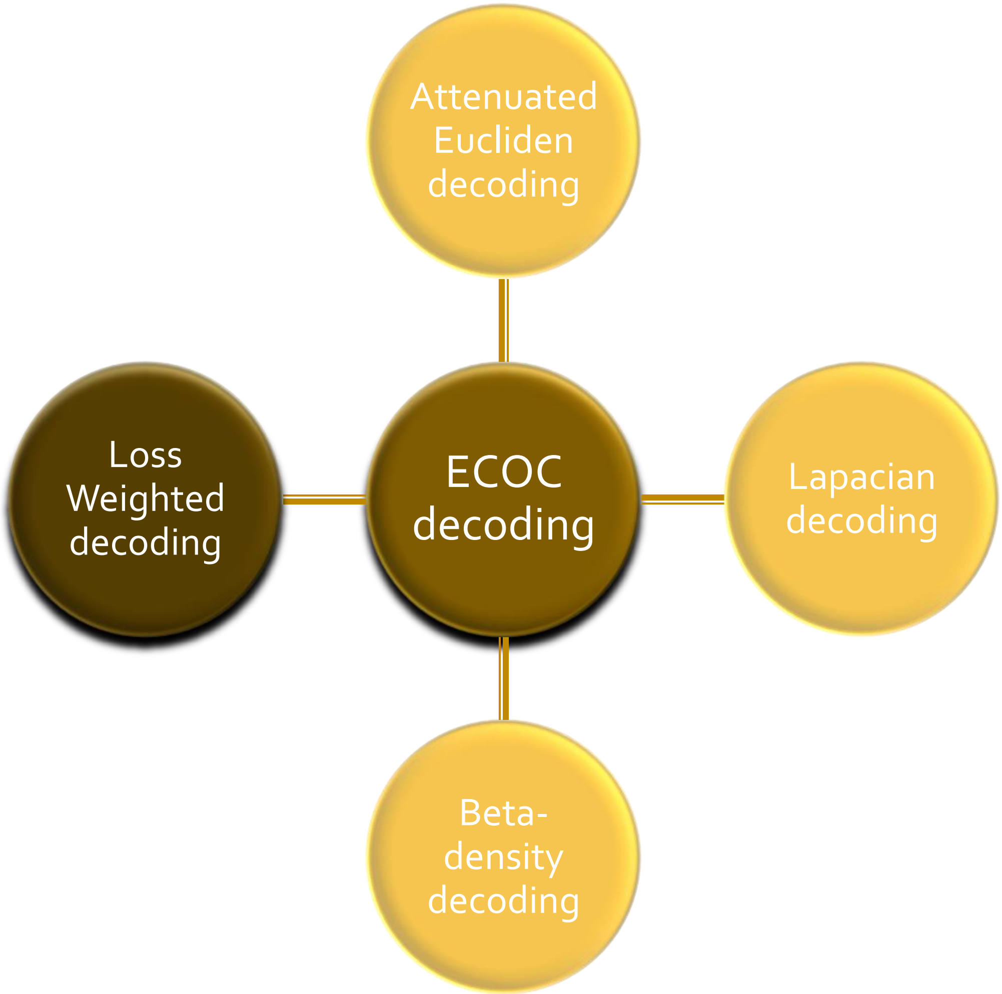
where u is a threshold parameter. We fixed u=1/3 to govern the uncertainty influence

Pessimistic Beta-Density Distribution decoding



- The approach correctly classifies the example
- The confidence grows with the sharpeness of the PDF

ECOC decoding – Our proposal



Loss-Weighted decoding

- **Motivation** : decoding decomposition, defining a matrix that weights the decoding process to assure that the hypotheses are fulfilled

$$d = M_W \cdot T \quad , T \;\; \textit{decoding measure}$$

Step 1

- Compute the matrix of hypothesis H

$$M = \begin{bmatrix} 1 & 1 & -1 & 0 \\ 1 & -1 & 0 & 0 \\ 1 & 1 & 1 & -1 \end{bmatrix}$$

$$H = \begin{bmatrix} 0.955 & 0.955 & 1.000 & 0.000 \\ 0.900 & 0.800 & 0.000 & 0.000 \\ 1.000 & 0.905 & 0.805 & 0.805 \end{bmatrix}$$

Step 2

- Normalize H to obtain a matrix M_W of PDF-rows

$$M_W = \begin{bmatrix} 0.328 & 0.328 & 0.344 & 0.000 \\ 0.529 & 0.471 & 0.000 & 0.000 \\ 0.285 & 0.257 & 0.229 & 0.229 \end{bmatrix}$$

Step 3

- Use M_W to weight the decoding process in a Loss-based decoding

$$d(\wp, i) = \sum_{j=1}^{n} M_W(i,j) L(M(i,j) \cdot f(\wp, j))$$

Summary

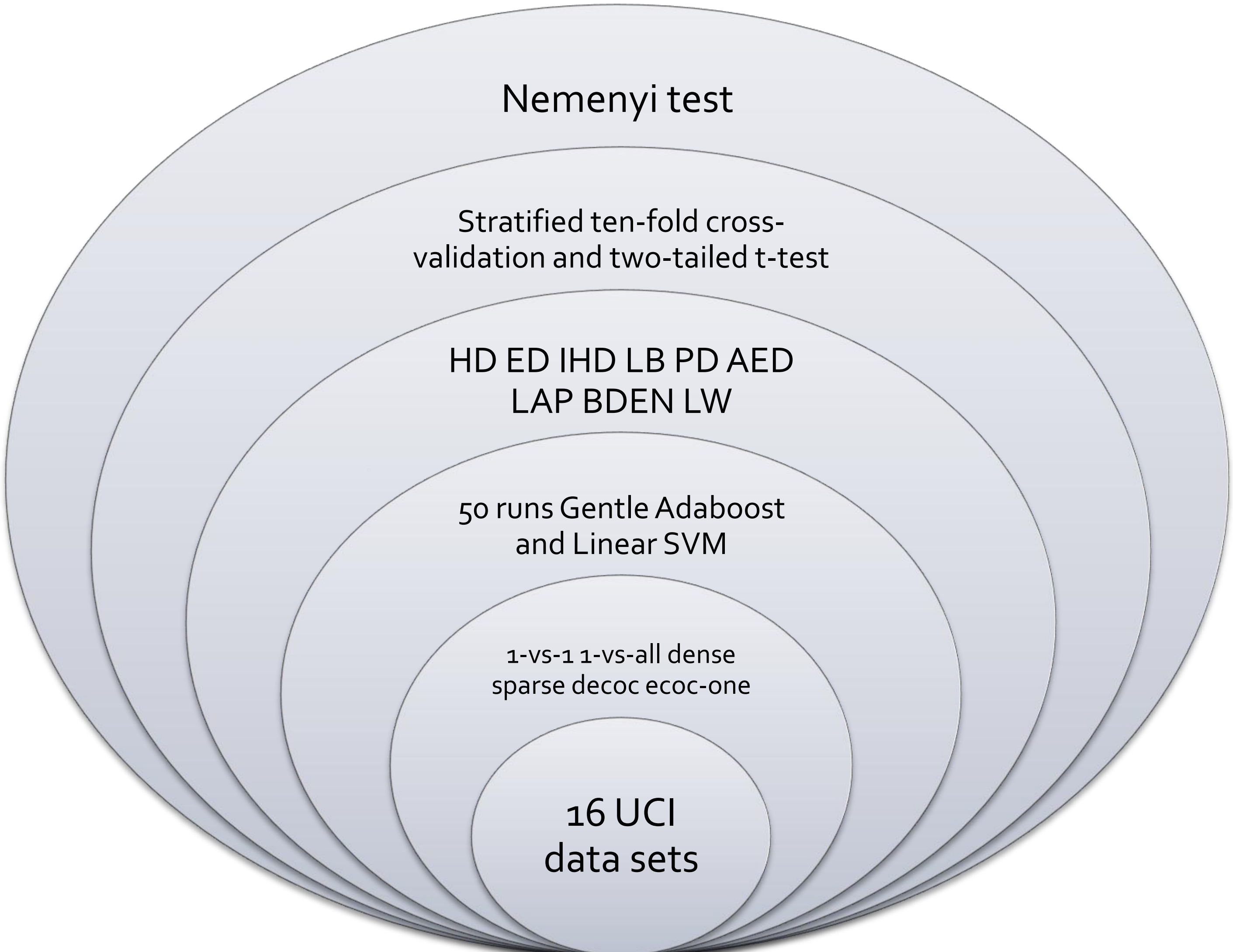
	$b \neq 0$	$b = 0$
Different *dynamic ranges*	Type 0	Type I
Same *dynamic ranges*	Type II	Type III

$$d = \sum_{k \in I_b} b_k + \sum_{i \in I_a} a_i + \sum_{j \in I_e} e_j$$

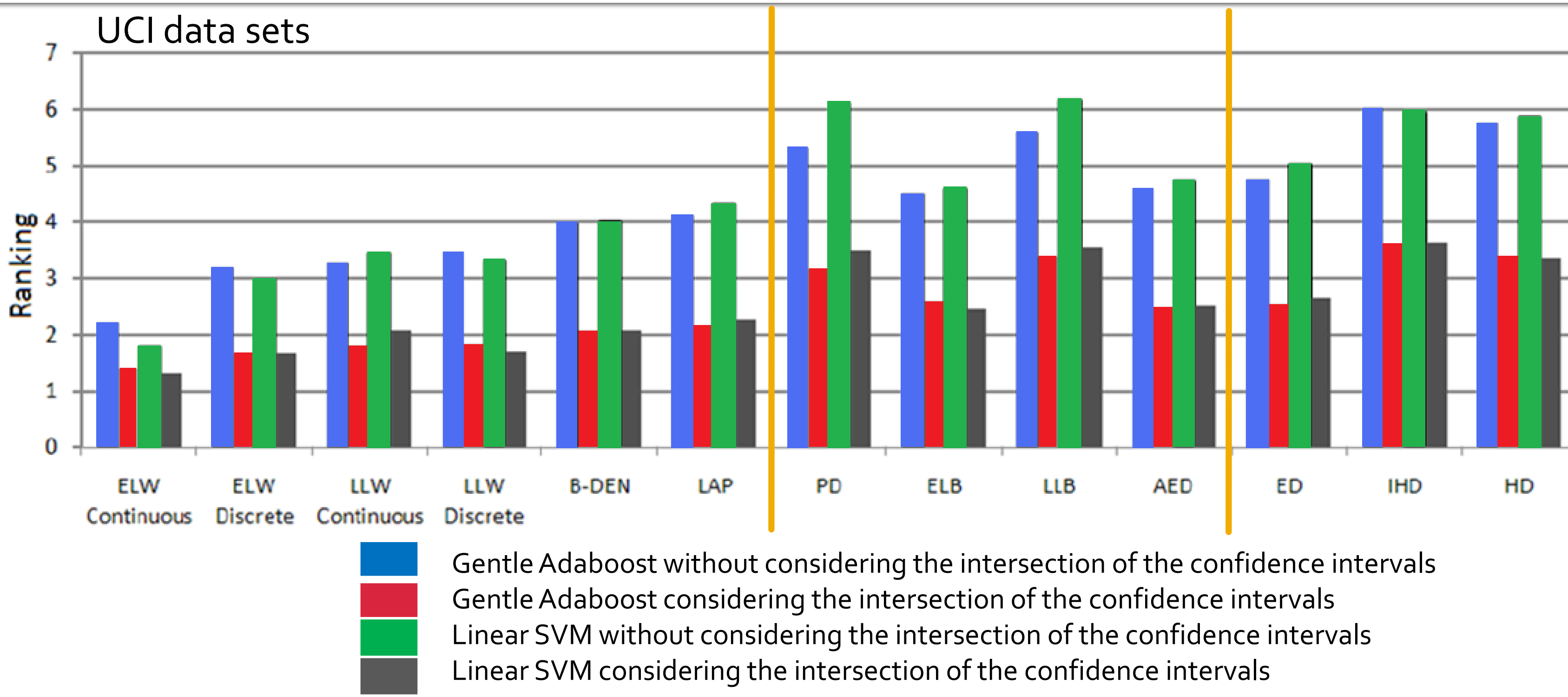
b – Value of a zero comparison
a – Value of a maching
e – Value of a failure
I_b, I_a, I_e - Index

Strategy	b	a	e	
AED	0	0	4	Type I
$\beta - DEN$	0	$\log(\nu)$	$\log(1-\nu)$	Type III
LLW_C	0	$-M_W(\_, i)\|f(\rho)\|$	$M_W(\_, j)\|f(\rho)\|$	Type III
LLW_D	0	$-M_W(\_, i)$	$M_W(\_, j)$	Type III
ELW_C	0	$\frac{M_W(\_, i)}{\mathbf{e}^{\|f(\rho)\|}}$	$M_W(\_, j)\mathbf{e}^{\|f(\rho)\|}$	Type III
ELW_D	0	$\frac{M_W(\_, i)}{\mathbf{e}}$	$M_W(\_, j)\mathbf{e}$	Type III

Decoding evaluation

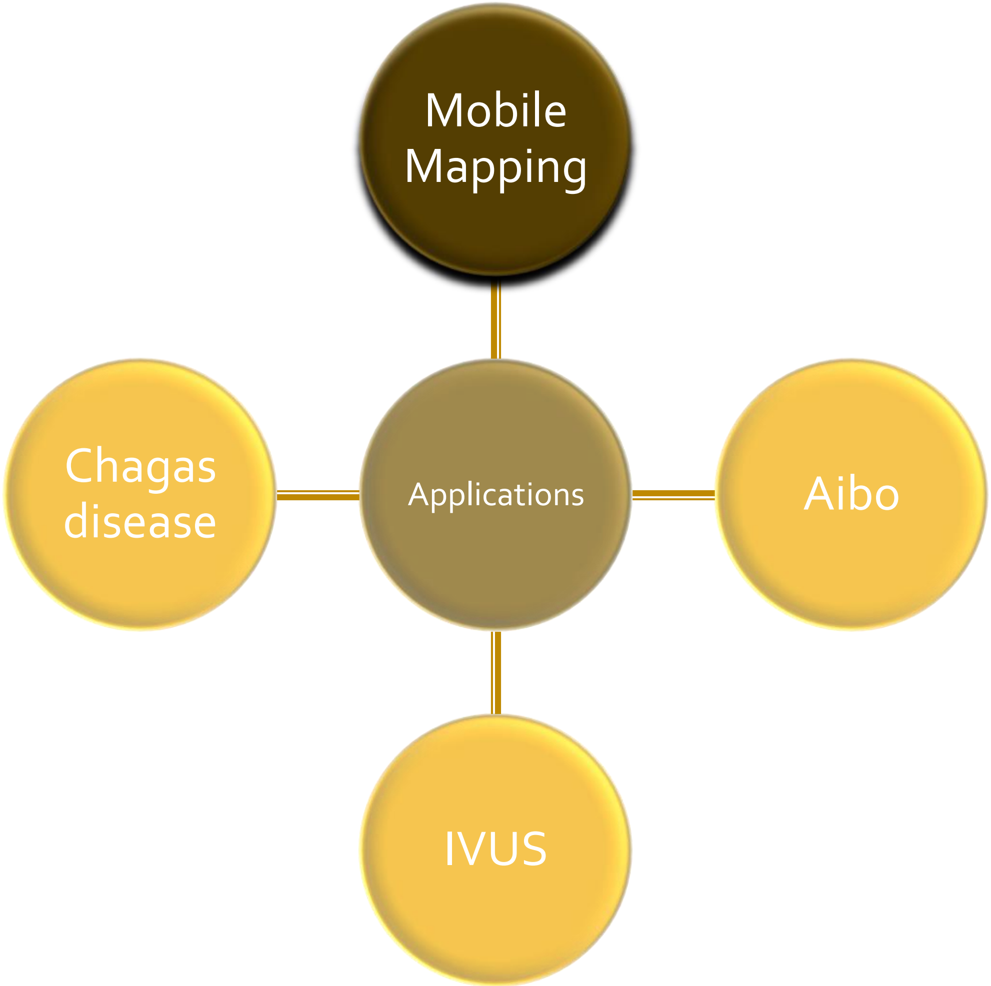


Decoding evaluation



Ranking	Gentle Adaboost			Linear SVM		
	Type 0	Type I	Type III	Type 0	Type I	Type III
Discrete	5.5000	4.9844	3.3715	5.6042	5.3880	3.2951
Continuous	3.0799	2.7839	**1.7813**	3.2778	3.0469	**1.8681**

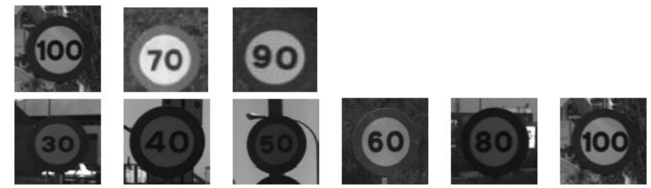
Applications



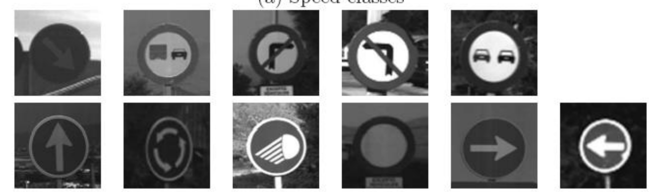
Mobile Mapping System

ICC Institut Cartogràfic de Catalunya

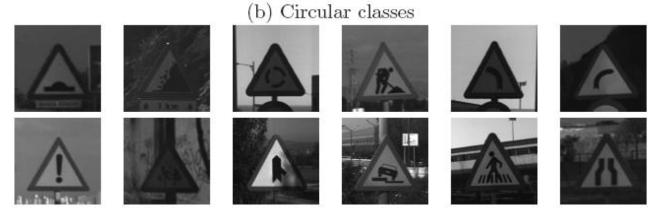
[Baro04]



(a) Speed classes



(b) Circular classes



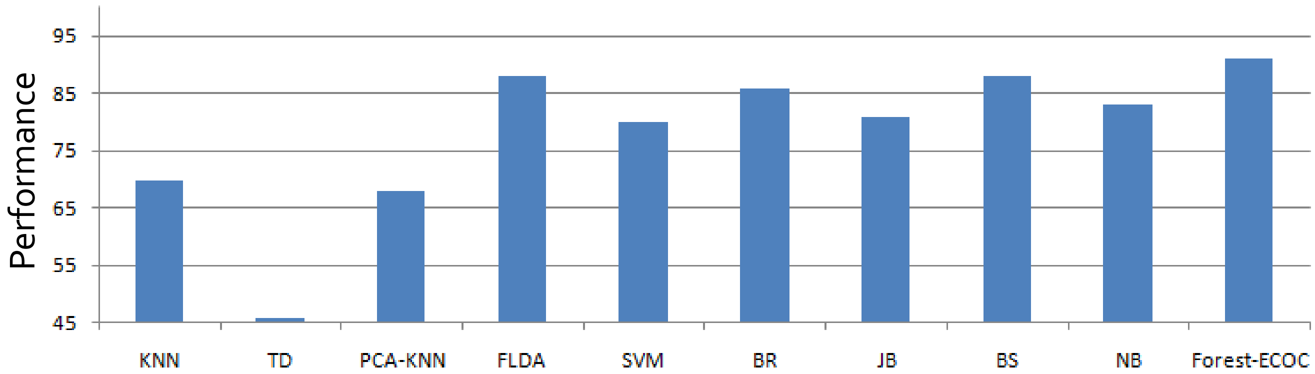
(c) Triangular classes

Dataset	#Training examples	#Test examples	#Features	#Classes
Circular	750	200	1225	12
Speed	500	200	1681	7
Triangular	750	200	1716	12

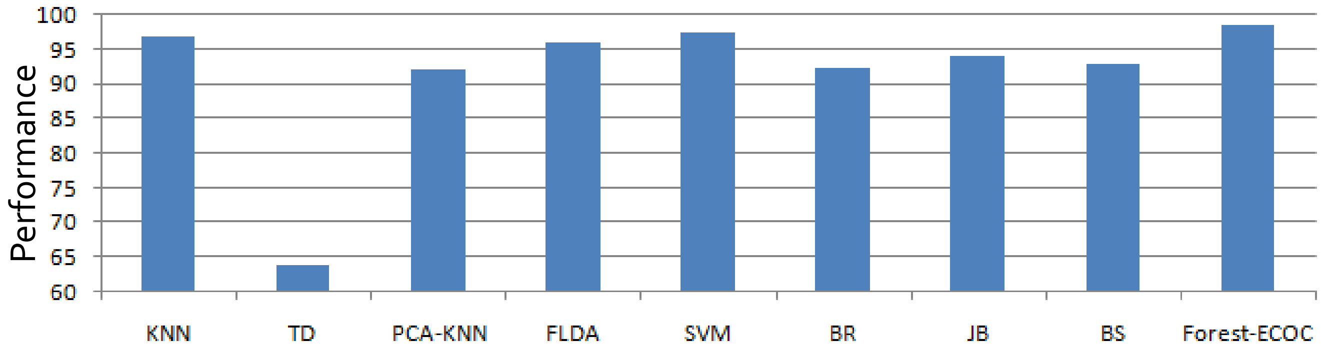
[Baro04] X. Baró and J. Vitrià, "Fast Traffic Sign Detection on greyscale images". 7è Congrés Català d'Intel·ligència Artificial, Barcelona. In press: Recent Advances in Artificial Intelligence Research and Development, Frontiers in Artificial Intelligence and Applications, 113:209-216. IOS Press, ISBN: 978-1-58603- 466-5. October 2004.

Mobile Mapping – Forest-ECOC

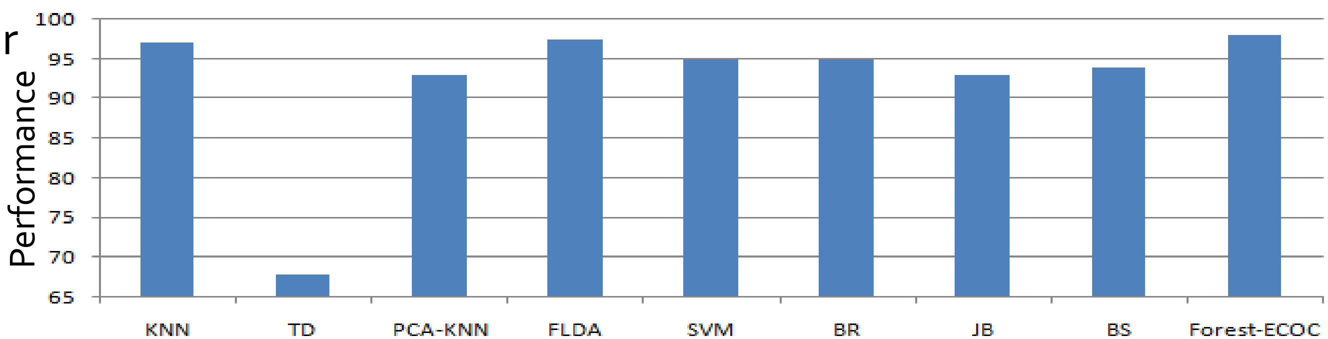
Speed



Circular



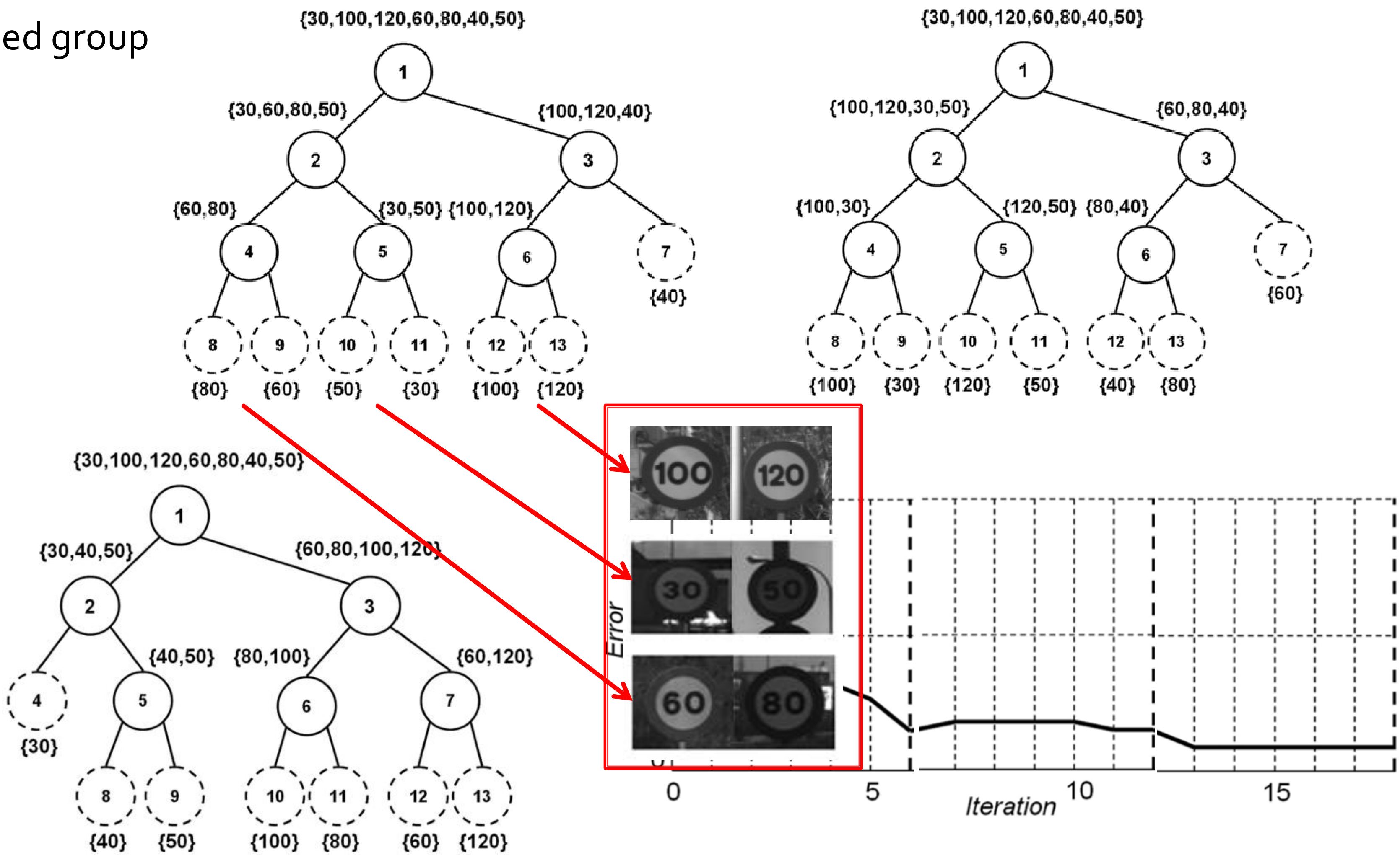
Triangular



KNN
TD – Tangent Distance
PCA-KNN
FLDA – Fisher+PCA
SVM – Linear SVM
BR – Gentle & Haar-like
JB – Joint Boosting
BS – Boosting Sampling
NB – Naive Bayes
Adaboost
Forest-ECOC

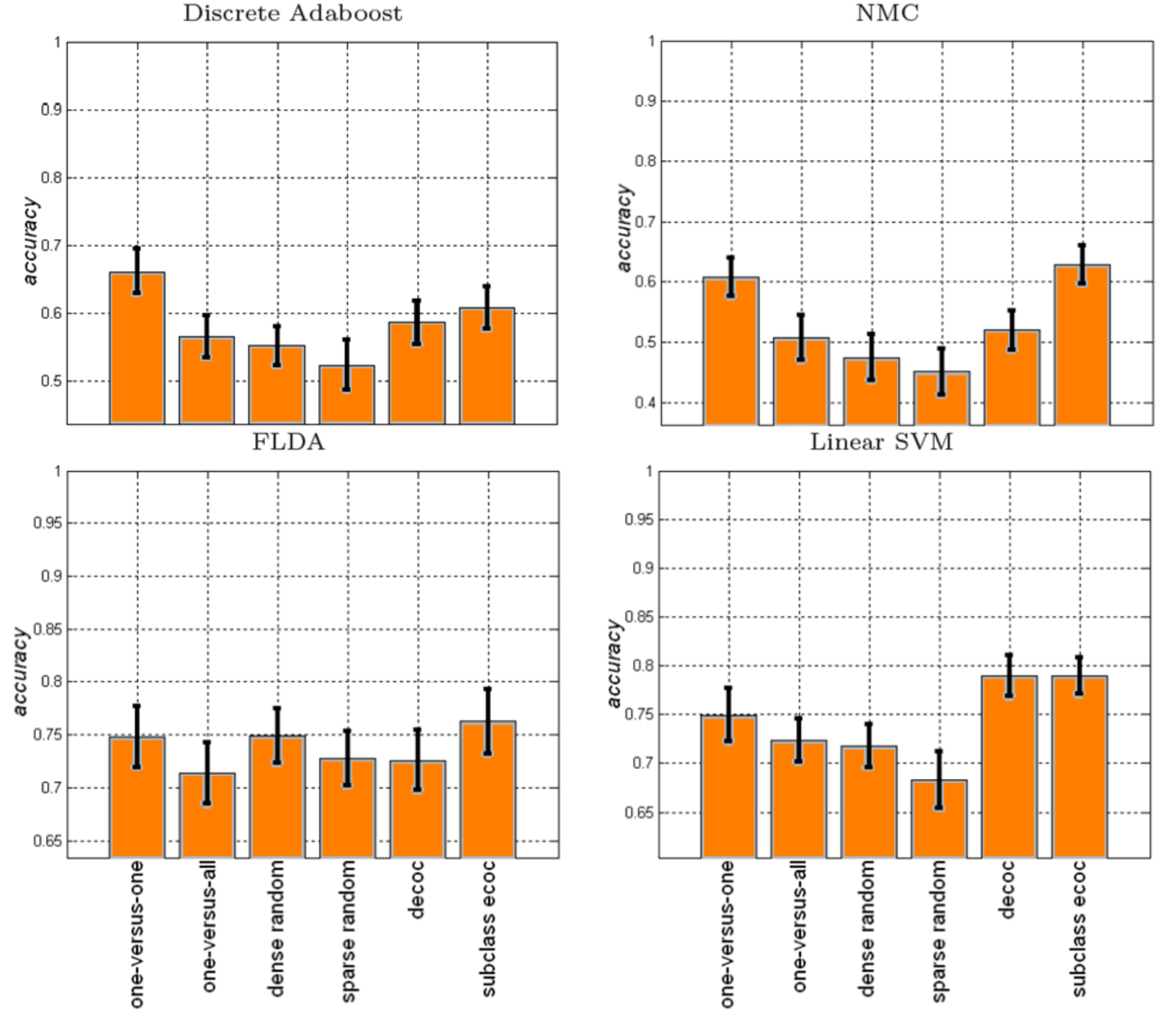
Mobile Mapping – Forest-ECOC

Speed group

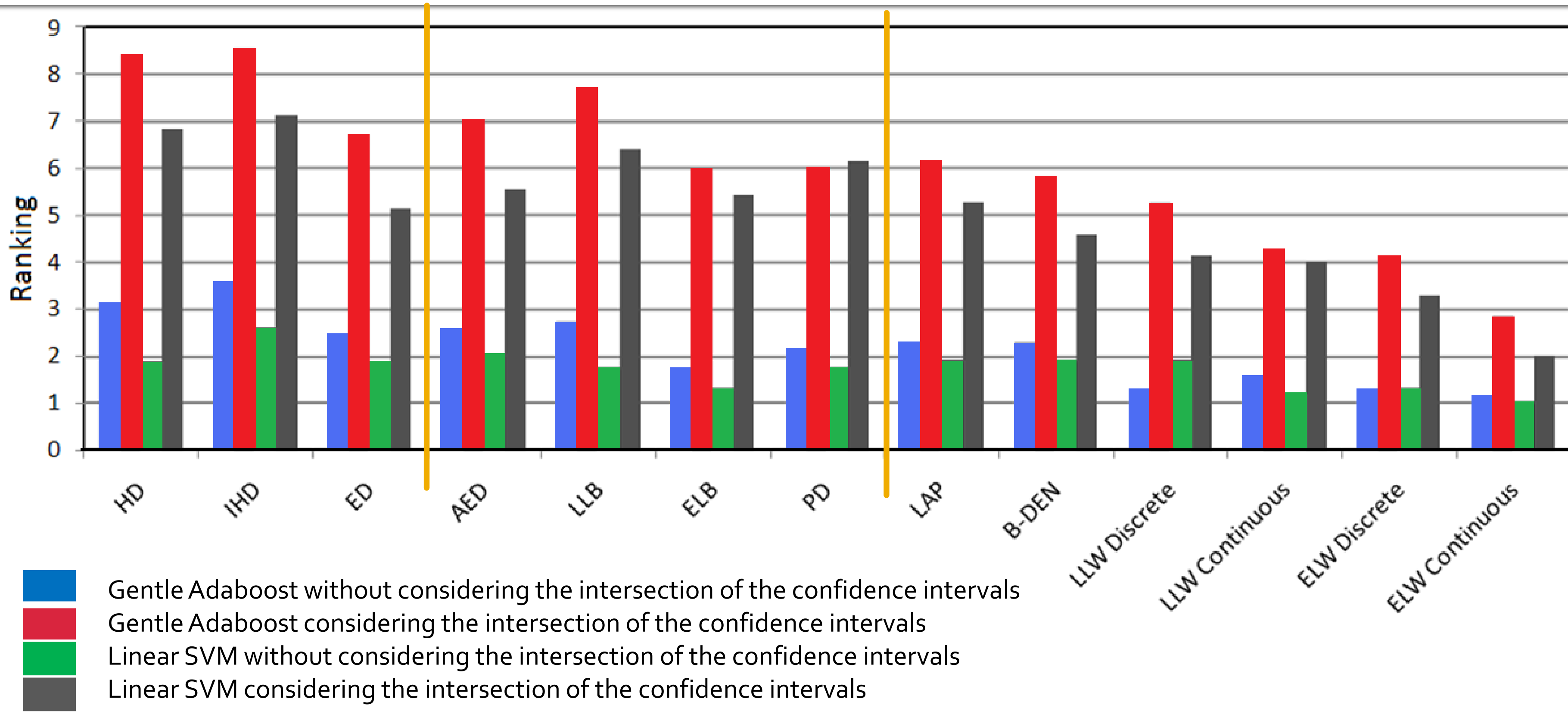


Mobile Mapping – Sub-class ECOC

	one-versus-one	one-versus-all	dense	sparse	DECOC	Sub-class ECOC
Global rank	1.8	3.6	3.4	4.6	2.6	1.2

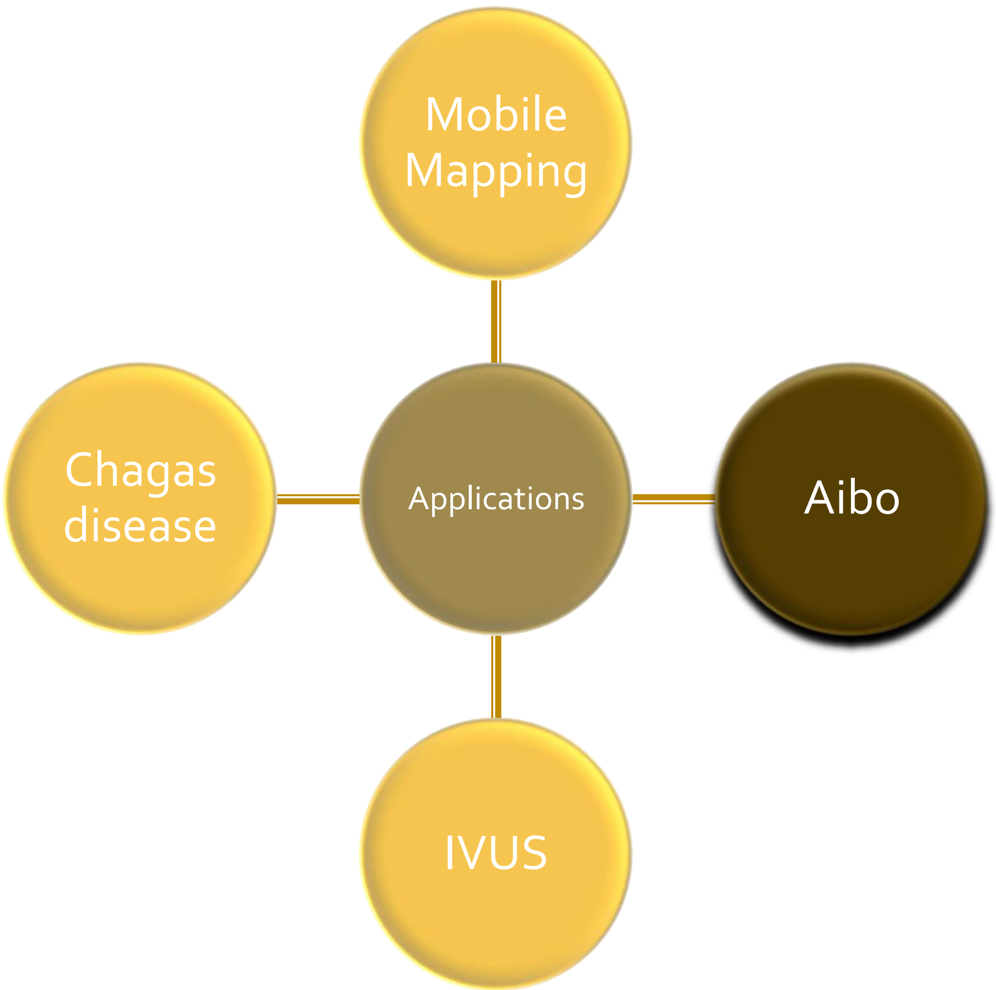


Mobile Mapping – Decodings



- Coding: one-versus-one, one-versus-all, dense random, sparse random, decoc, ecoc-one
- Decoding: HD, ED, IHD, LLB, ELB, PD, AED, LAP, BDEN, LLW, ELW.
- Validation: stratified ten-fold cross-validation and test for the confidence interval with a two-tailed t-test

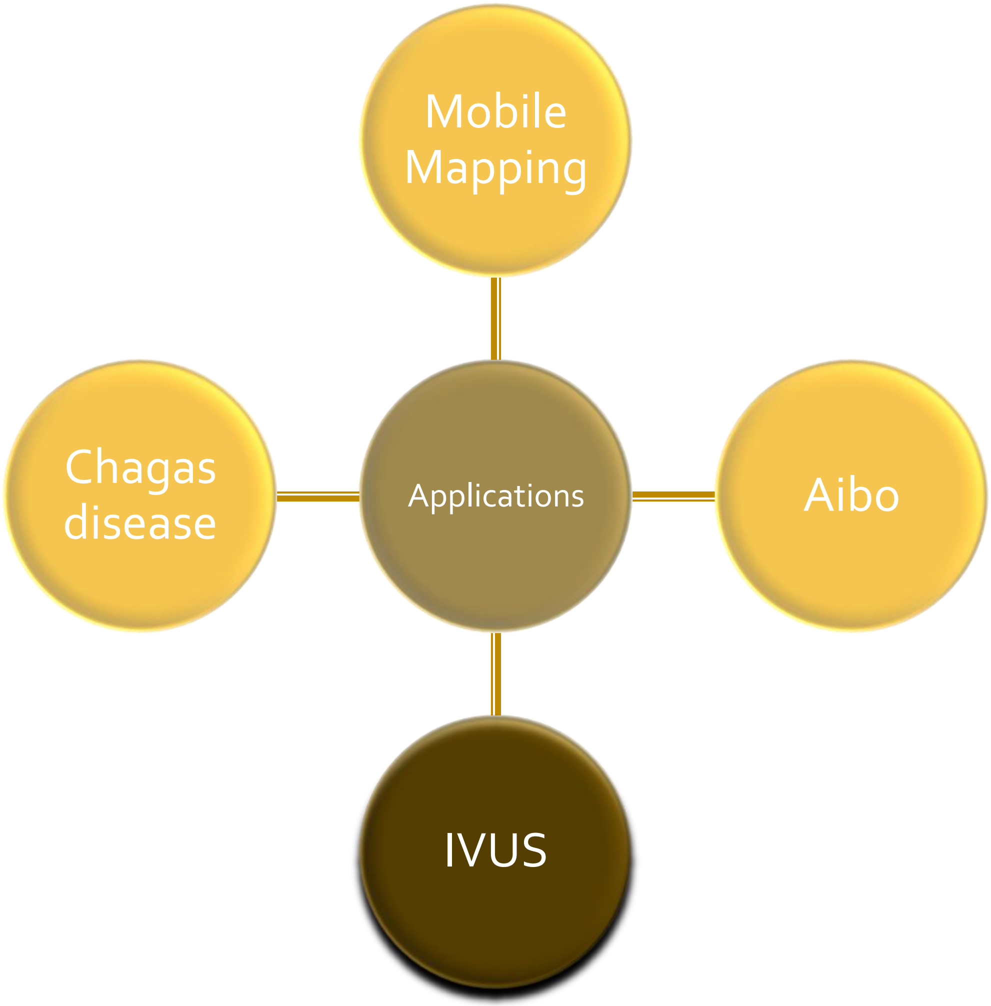
Applications



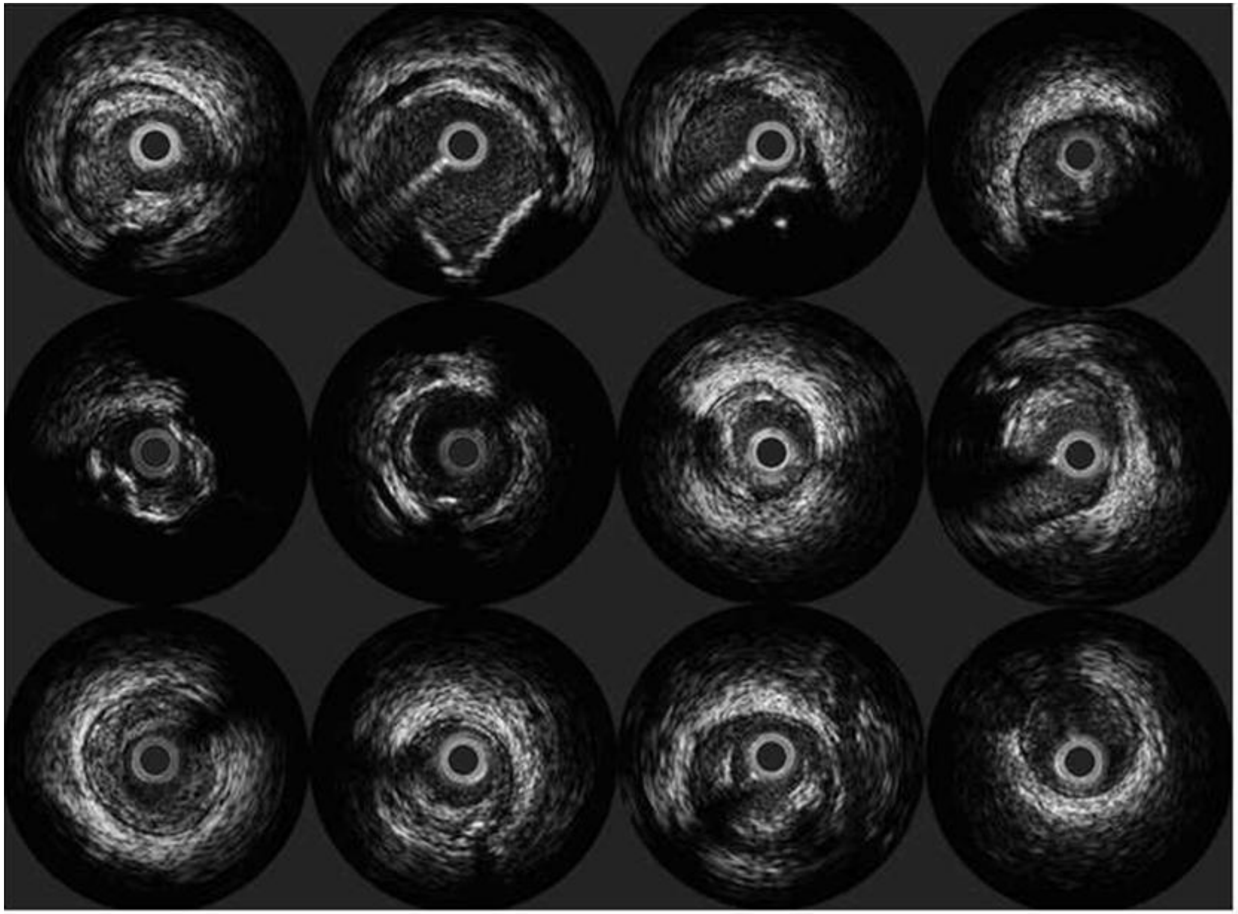
Aibo

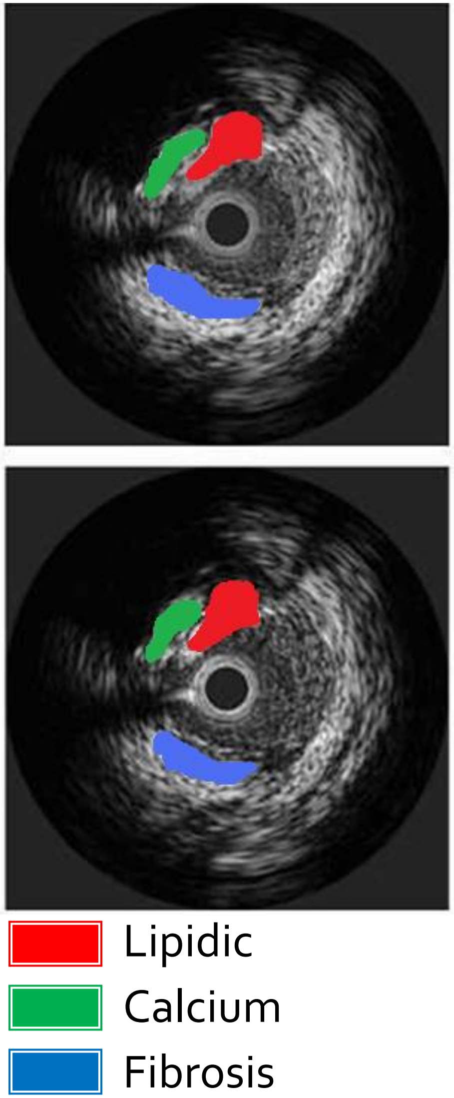
- Sony Aibo robot
- Multi-class syntethic signs detection by means of Adaboost with a Cascade of weak classifiers
- ECOC classification

Applications



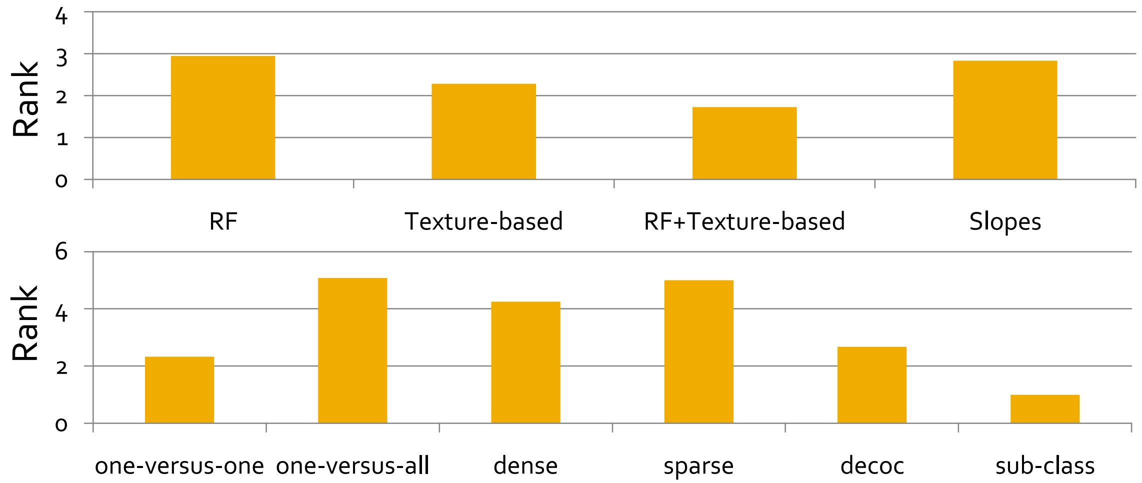
IVUS





IVUS

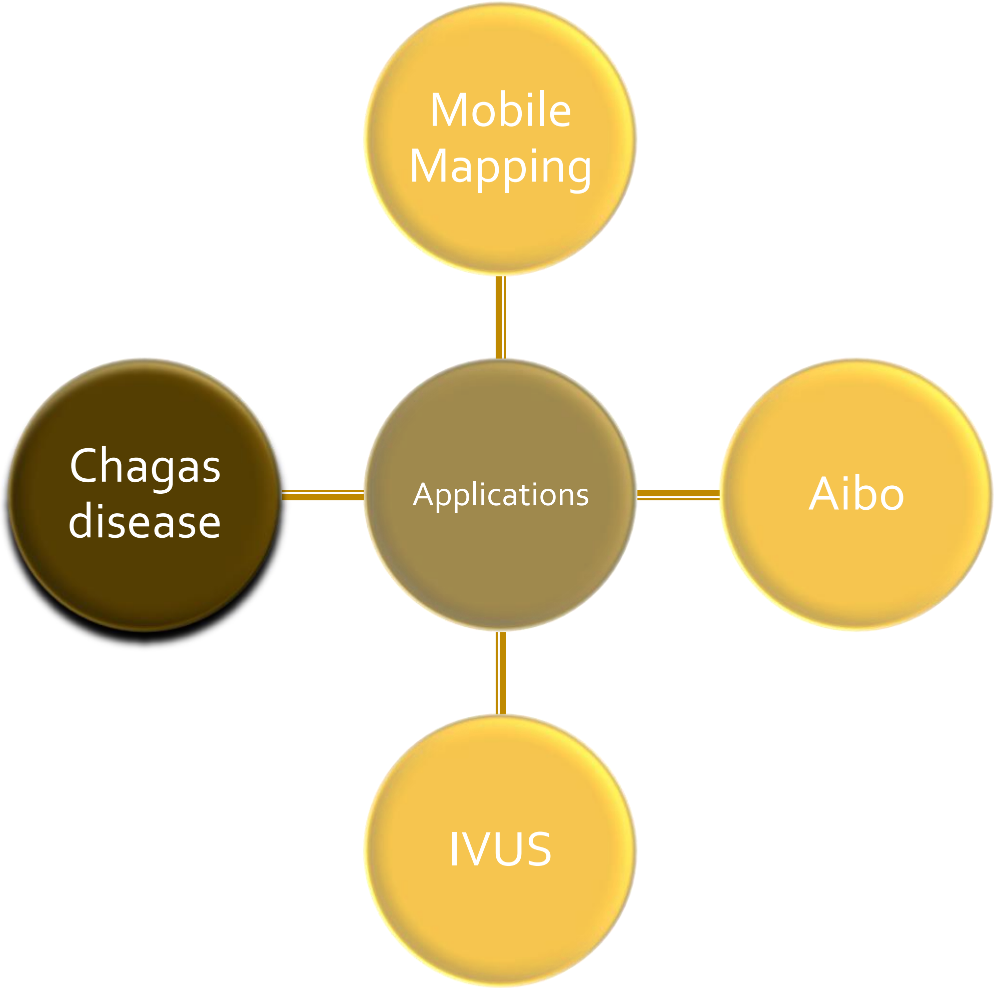
- Features
  - RF, Slope, and Texture-based features **[Karla06]**
- Data set
  - We used the RF signals and their reconstructed images from a set of 10 different patients with Left Descent Artery pullbacks acquired in Hospital "German Trias i Pujol" from Badalona, Spain.



- Statistical significance of sub-class strategy using **Friedman** and **Nemenyi** tests

[Karla06] K. Caballero, J. Barajas, O. Pujol, N. Salvatella, and P. Radeva. In-vivo ivus tissue classification: a comparison between rf signal analysis and reconstructed images. In Progress in Pattern Recognition, pp. 37–146. Springer Berlin / Heidelberg, 2006.

Applications



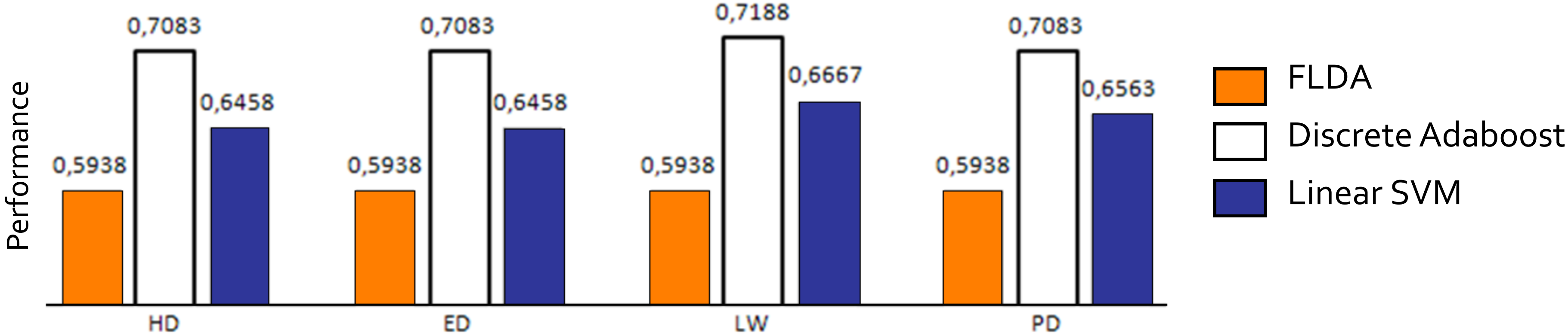
Chagas disease

(a) (b)

(a) Triatoma and (b) adult Rhodnius prolixus, a kissing bug.

Tripomastigote and bloodstream trypomastigotes.

- QRS Slope features **[Pueyo07]**
- 107 individuals grouped based on their degree of coronary damage
- Simon Bolivar University (Venezuela)



[Pueyo07] E. Pueyo, E. Anzuola, E. Laciar, P. Laguna, and R. Jane, Evaluation of QRS slopes for determination of myocardial damage in chronic chagasic patients. Computers in Cardiology, 2007.

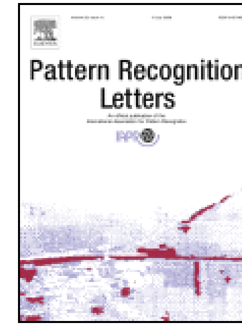
Conclusions

- Problem-dependent methodology to deal with the ECOC coding step:
  - Problem-dependent ECOC approaches yield compact codewords and thus lead to fast and robust classification rate avoiding overfitting
  - Forest-ECOC and ECOC-ONE extend the coding process based on the ensemble performance
  - Sub-class ECOC enriches the problem of ECOC design from the point of the view of the data
- Zero-bias free methodology to deal with the ECOC decoding:
  - Common taxonomy defined for all existing decoding strategies
  - Novel decoding strategies free from the zero bias proper to the classical ternary codewords that significantly improve the ECOC performance
  - Pessimistic Beta-Density Distribution decoding that gives a prediction based on modelling accuracy and uncertainty
  - Loss-Weighted decoding that overperforms other decoding strategies due to a weighting matrix applicable to any existing decoding strategy
- Viability on real-life applications

Future work

- Correspondence ECOC design versus base classifier
- Continuous ECOC construction
  - Binary → ternary → continuous
- Faster alternatives to ECOC coding designs constructions
- ECOC Public-domain toolbox

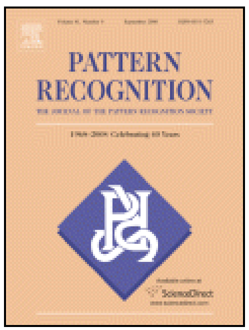
Relevant publications



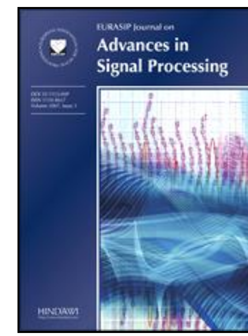
Coding:

S. Escalera, D. Tax, O. Pujol, P. Radeva, and R. Duin, **Subclass** Problem-dependent Design of Error-Correcting Output Codes. In TPAMI, vol. 8, issue 6, pp. 1041-1054, 2008,

S. Escalera, O. Pujol, and P. Radeva. Boosted Landmarks of Contextual Descriptors and **Forest-ECOC**: a novel framework to detect and classify objects in cluttered scenes. In PRL, vol 28/13, pp 1759-1768, 2007.

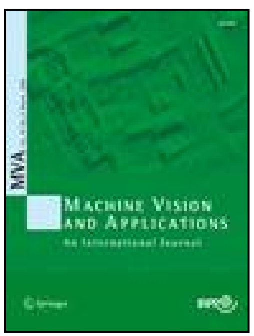


O. Pujol, S. Escalera, and P. Radeva. **Optimal Node Embedding** in Error Correcting Output Codes. In PR, vol. 14, issue 2, pp.713-725, 2008.



Decoding:

S. Escalera, O. Pujol, and P. Radeva, Traffic Sign Recognition System with **Beta-Correction**. In Machine Vision and Applications.



Applications:

X. Baró, S. Escalera, J. Vitrià, O. Pujol, and P. Radeva, Traffic Sign Recognition using Evolutionary Adaboost detection and **Forest-ECOC** classification. In IEEE Transactions on Intelligent Transportation Systems.

S. Escalera, O. Pujol, J. Mauri, and P. Radeva, Intravascular Ultrasound Tissue Characterization with **Sub-class** Error-Correcting Output Codes Article, Journal of Signal Processing Systems.

S. Escalera, O. Pujol, and P. Radeva, **Complex Salient Regions** for Computer Vision Problems. In EURASIP, ID 451389, 2008.

And more than 15 conference papers…

Centre de Visió per Computador

Thank you!!

Author: Sergio Escalera Guerrero

Advisors: Dr. Oriol Pujol Vila and Dr. Petia Radeva

9 / 7 / 2008