Compact Evolutive Design of Error-Correcting Output Codes

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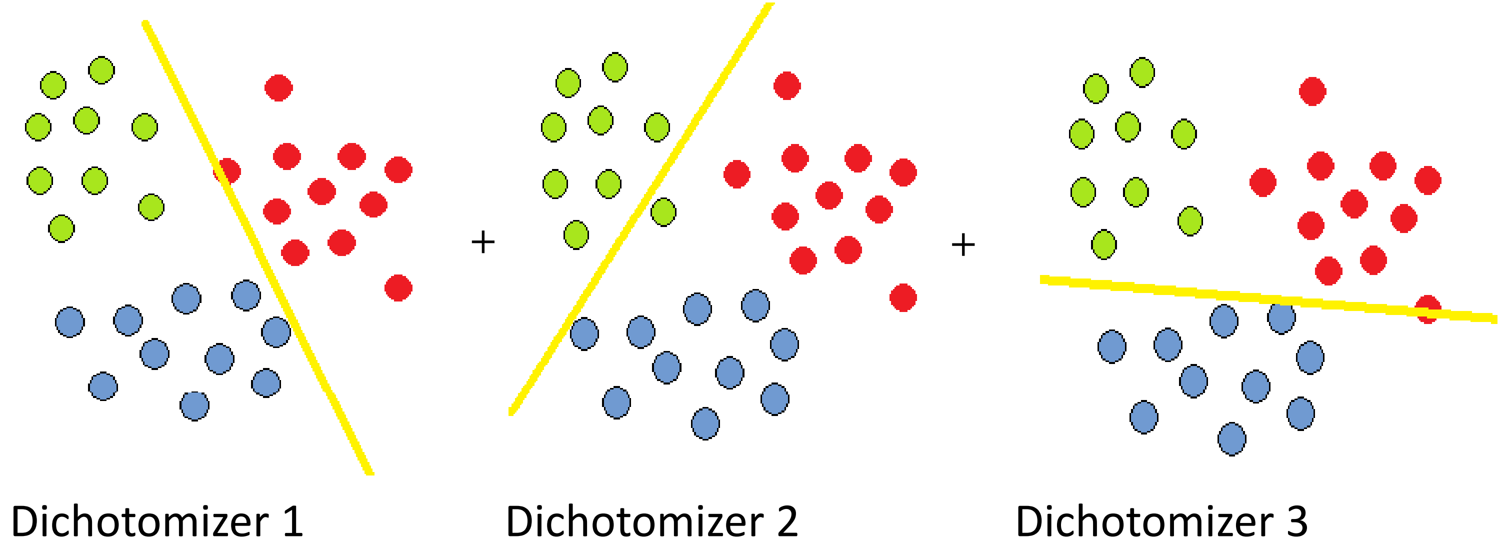
Outline

- Error Correcting Output Codes
- SVMs with Gaussian-RBF kernel
- Genetic optimization
- Experiments & results
- Conclusions

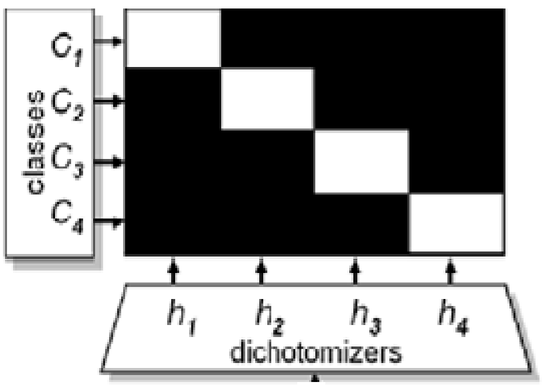
Error Correcting Output Codes (ECOC)

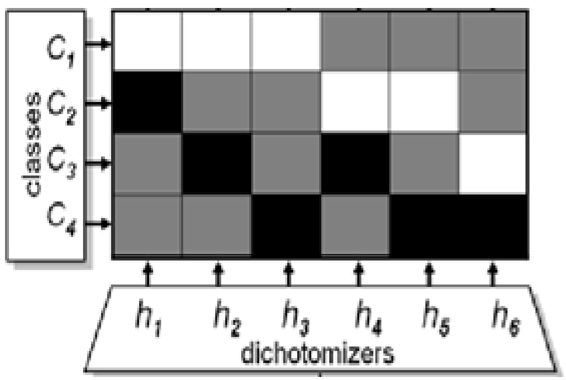
- ECOCs are an ensemble learning methodology which allow to combine dichotomizers to treat multiclass problems.



ECOC coding

- ECOCs can be represented as matrices, which columns represent the different sub-problems to treat.
- Each column has values that distinguish categories in two groups.
- One-versus-All and One-versus-One are the standard codings.

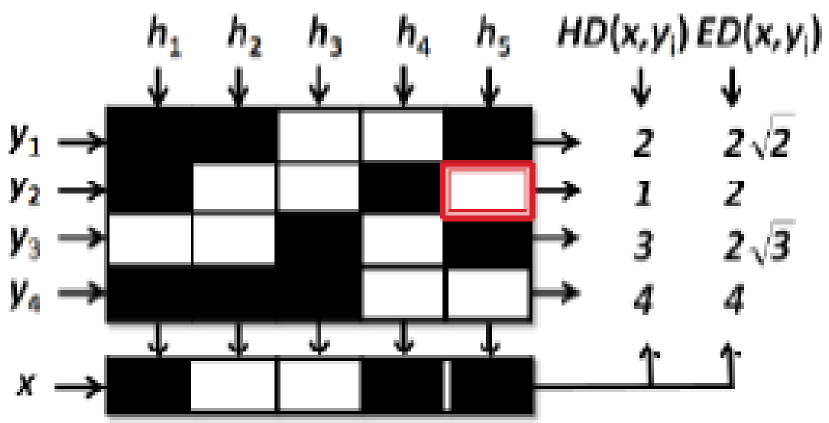




ECOC decoding

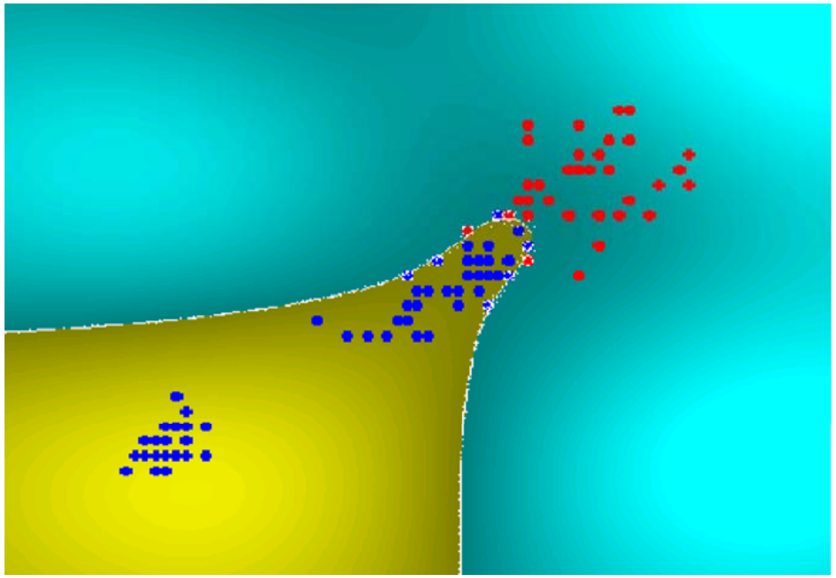
- Each sub-problem is trained and the set of predictions are compared to the codewords.

- Various types of decoding based on Euclidean and Hamming distances (only binary codings).

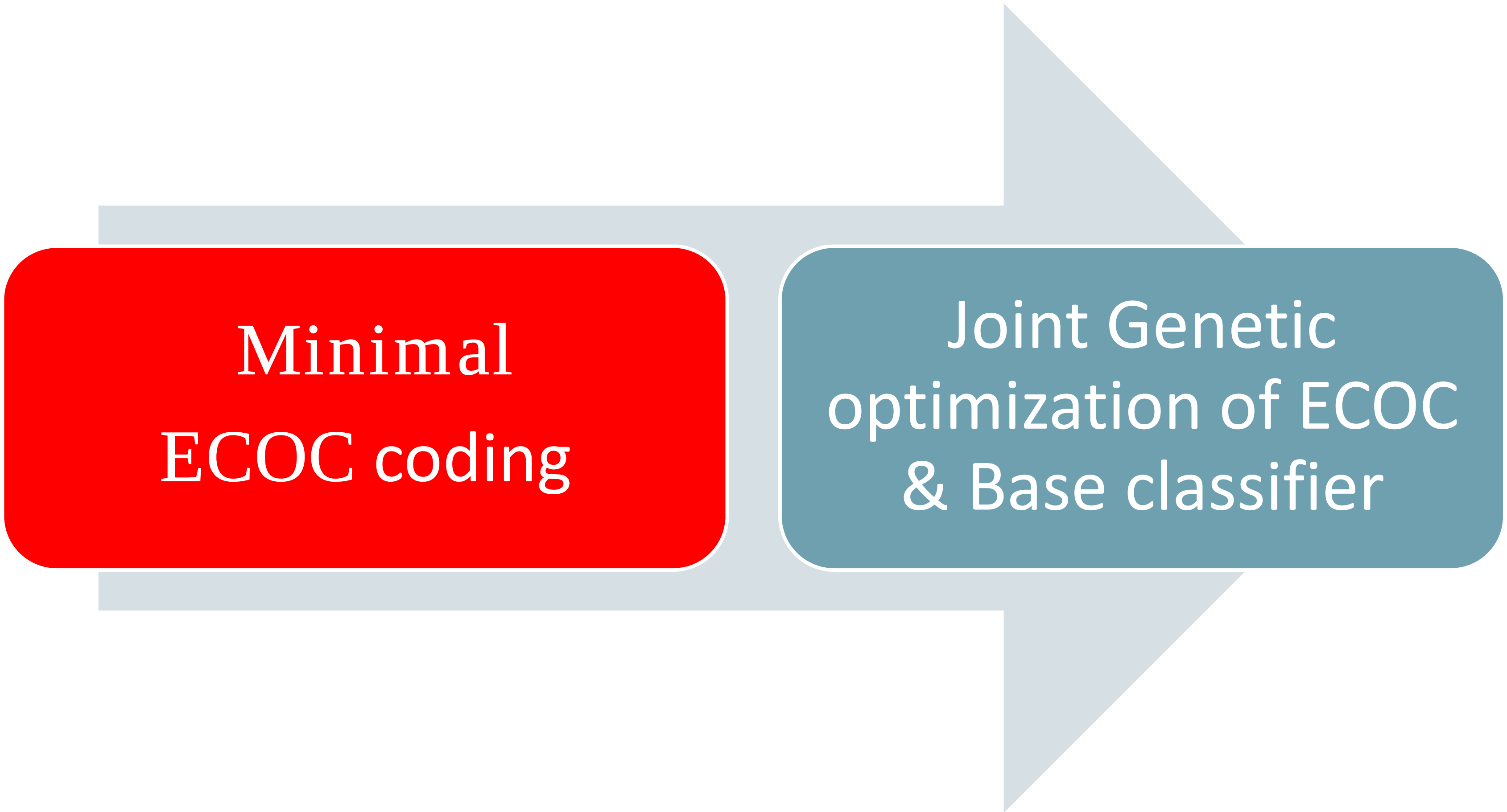


Base classifier: SVM with an RBF kernel

- Each binary problem is learned by a base classifier.
- SVM with RBF kernels have shown a good performance on those kind of problems.
- This type of SVM needs the parameters (C & Gamma) to be optimized.

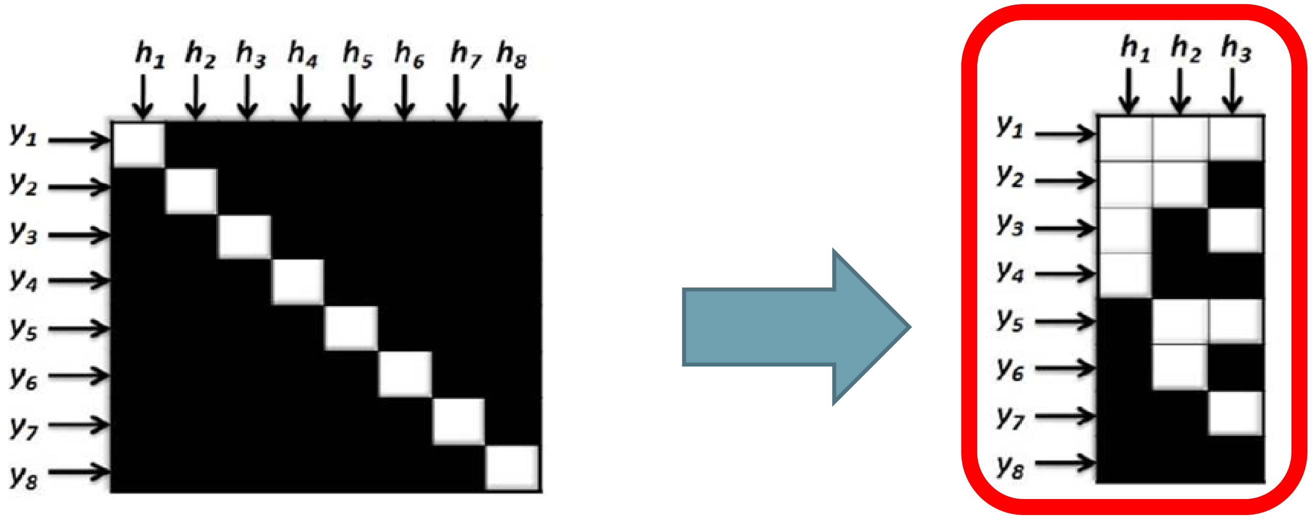


Global overview

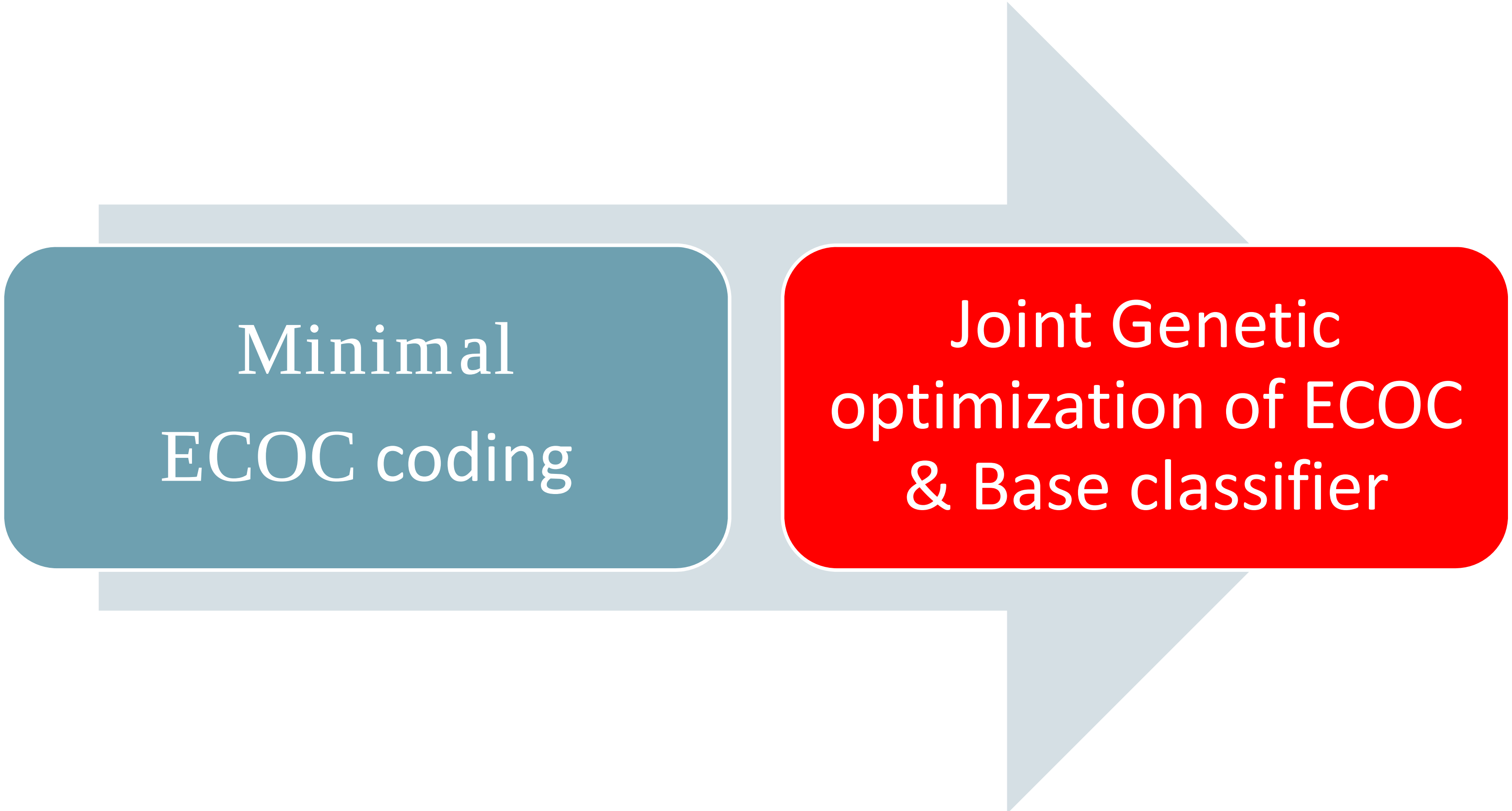


Minimal coding

- Define the minimal number of base classifiers needed to discriminate N categories.
- Taking profit of Information theory only $\log_2 N$ bits are needed to discriminate N categories.

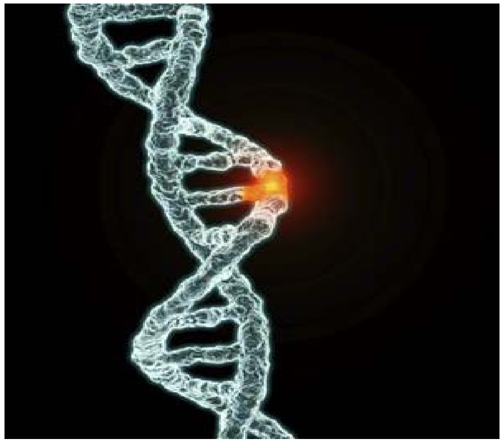


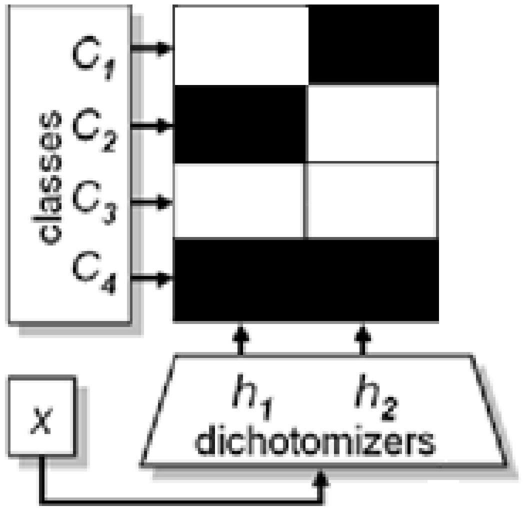
Global overview



Genetic algorithms

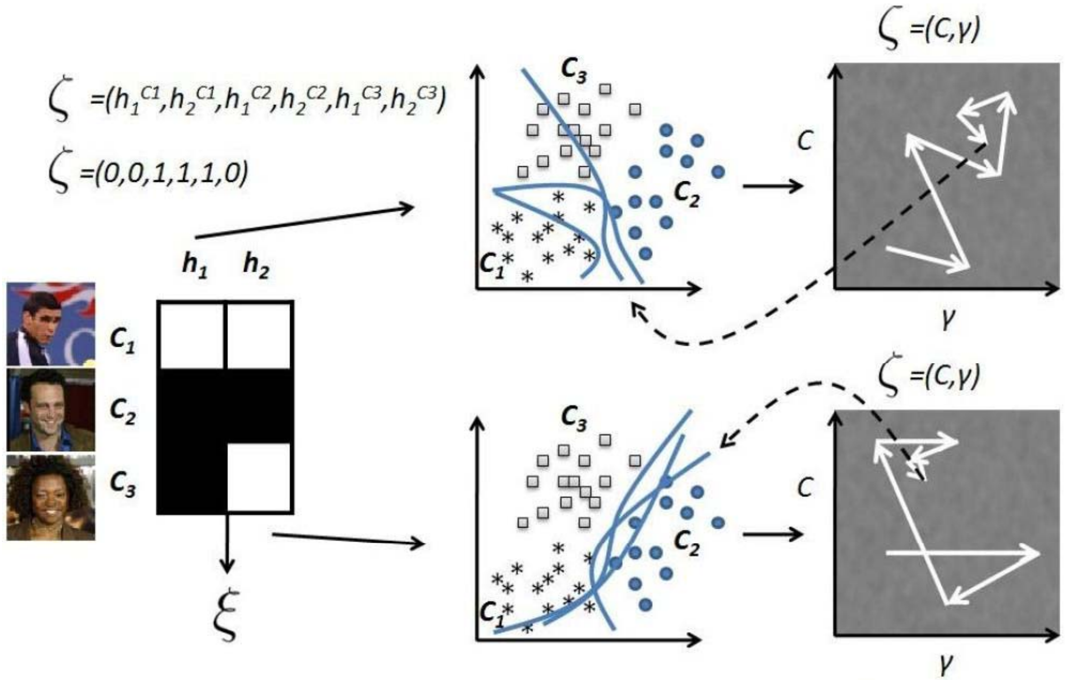
- Optimization algorithms based on the evolution theory of Darwin.
- Recommendable method when the space is not continuous neither differentiable.





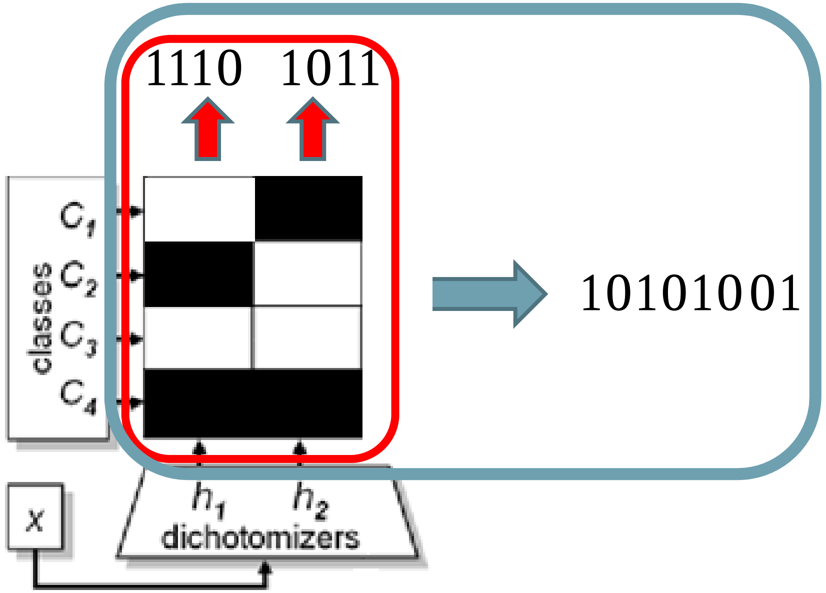
Evolutionary optimization for SVMs

- An optimization process is carried out to tune the parameters of the SVMs.
- SVM-RBF classifiers have mainly 2 parameters (C & Gamma).



Evolutionary optimization for ECOCs

- Each ECOC individual is seen as a binary vector and evaluated by means of its classification error.



A) Optimize the SVMs looking for suitable parameters.

B) Optimize the coding matrix and return to step A.

- Standard genetic operators are used, scattered crossover and gaussian add unit mutation.

Experiments characteristics

- UCI dataset characteristics.

Problem	#Training samples	#Features	#Classes
Dermathology	366	34	6
Iris	150	4	3
Ecoli	336	8	8
Vehicle	846	18	4
Wine	178	13	3
Segmentation	2310	19	7
Glass	214	9	7
Thyroid	215	5	3
Vowel	990	10	11
Balance	625	4	3
Shuttle	14500	9	7
Yeast	1484	8	10

- Labelled Faces in The Wild : 6144x50, 184 classes (http://vis-www.cs.umass.edu/lfw/).

Results on UCI problems

- As we can see the evolutive minimal performs better than the standard codings.

	Binary Minimal ECOC		Evol. Minimal ECOC		one-vs-all ECOC		one-vs-one ECOC	
Data set	Perf.	Classif.	Perf.	Classif.	Perf.	Classif.	Perf.	Classif.
Derma	96.0±2.9	3	**96.3±2.1**	3	95.1±3.3	6	94.7±4.3	15
Iris	96.4±6.3	2	**98.2±1.9**	2	96.9±6.0	3	96.3±3.1	3
Ecoli	80.5±10.9	3	**81.4±10.8**	3	79.5±12.2	8	79.2±13.8	28
Vehicle	72.5±14.3	2	76.99±12.4	2	74.2±13.4	4	**83.6±10.5**	6
Wine	95.5±4.3	2	**97.2±2.3**	2	95.5±4.3	3	**97.2±2.4**	3
Segment	96.6±2.3	3	96.6±1.5	3	96.1±1.8	7	**97.18±1.3**	21
Glass	56.7±23.5	3	50.0±29.7	3	53.85±25.8	6	**60.5±26.9**	15
Thyroid	**96.4±5.3**	2	93.8±5.1	2	95.6±7.4	3	96.1±5.4	3
Vowel	57.7±29.4	3	**81.78±11.1**	3	80.7±11.9	8	78.9±14.2	28
Balance	80.9±11.2	2	87.1±9.2	2	89.9±8.4	3	**92.8±6.4**	3
Shuttle	80.9±29.1	3	83.4±15.9	3	**90.6±11.3**	7	86.3±18.1	21
Yeast	50.2±18.2	4	**54.7±11.8**	4	51.1±18.0	10	52.4±20.8	45
Rank & #	2.9	**2.7**	**2.0**	**2.7**	2.7	5.7	2.2	15.9

Results on LFW dataset

- In this experiment we can see how evolutionary approaches outperform standard ECOC codings while decreasing the number of classifiers dramatically.

	Binary M. ECOC		GA M. ECOC		one-vs-all		one-vs-one	
Data set	Perf.	#	Perf.	#	Perf.	#	Perf.	#
FacesWild	26.4±2.1	10	**30.7±2.3**	10	25.0±3.1	184	-	16836

Conclusions

- The minimal ECOC represents the lower-bound in terms of number of classifiers.
- The evolutive ECOC optimization obtains comparable results to the standard coding designs (sometimes better) while using far less number of dichotomizers.
- This design is suitable when classifying problems with large number of classes.

Thank you

QUESTIONS?