

# Supplementary material for the paper “The mRMR variable selection method: a comparative study for functional data”

José R. Berrendero, Antonio Cuevas, José L. Torrecilla  
 Departamento de Matemáticas  
 Universidad Autónoma de Madrid, Spain

## 1 List of models used in the simulation study and a few example outputs

Our simulation study consists of 400 experiments based on 100 different underlying models. The optimal classification rule in each case depends only on a finite number of variables. Models differ in complexity and number of relevant variables. The processes involved are chosen among the following: first, the **standard Brownian Motion**,  $B$ . Second,  $BT$  denotes a **Brownian Motion with a trend**  $m(t)$ , i.e.,  $BT(t) = B(t) + m(t)$ ; we have considered several choices for  $m(t)$ , a linear trend,  $m(t) = ct$ , a linear trend with random slope, i.e.,  $m(t) = \theta t$ , where  $\theta$  is a Gaussian r.v., and different members of two parametric families: the *peak* functions  $\Phi_{m,k}$  and the *hillside* functions, defined by

$$\Phi_{m,k} = \int_0^t \varphi_{m,k}(s) ds \quad , \quad \text{hillside}_{t_0,b}(t) = b(t - t_0)\mathbb{I}_{[t_0,\infty)},$$

where,  $\varphi_{m,k}(t) = \sqrt{2^{m-1}} \left[ \mathbb{I}_{\left(\frac{2k-2}{2^m}, \frac{2k-1}{2^m}\right)} - \mathbb{I}_{\left(\frac{2k-1}{2^m}, \frac{2k}{2^m}\right)} \right]$  for  $m \in \mathbb{N}$ ,  $1 \leq k \leq 2^{m-1}$ . Third, the **Brownian Bridge**:  $BB(t) = B(t) - tB(1)$ . Our fourth class of Gaussian processes is the **Ornstein–Uhlenbeck process**, with zero mean ( $OU$ ) or different mean functions  $m(t)$  ( $OUt$ ). Finally some “smooth” processes have been also include. They are obtained by convolving Brownian trajectories with Gaussian kernels. We have considered two levels of smoothing denoted by sB and ssB.

In the following list of models,  $\mu_i$  denotes de distribution of  $X|Y = i$  and *variables* is the set of relevant variables in each Gaussian or Mixture case. We call them “relevant” in the sense that the optimal classification rule depends only on these variables. In the list below the variables written in boldface are “especially relevant” regarding their influence in the optimal classifier.

### 1. GAUSSIAN MODELS CONSIDERED:

$$1. \quad \mathbf{G1} : \begin{cases} \mu_0 : & B(t) \\ \mu_1 : & B(t) + \theta t \end{cases} \quad , \theta \sim N(0, 3)$$

$$\text{variables} = \{X_{100}\}.$$

$$3. \quad \mathbf{G2} : \begin{cases} \mu_0 : & B(t) + t \\ \mu_1 : & B(t) \end{cases}$$

$$\text{variables} = \{X_{100}\}.$$

$$2. \quad \mathbf{G1b} : \begin{cases} \mu_0 : & B(t) \\ \mu_1 : & B(t) + \theta t \end{cases} \quad , \theta \sim N(0, 5)$$

$$\text{variables} = \{X_{100}\}.$$

$$4. \quad \mathbf{G2b} : \begin{cases} \mu_0 : & B(t) + 3t \\ \mu_1 : & B(t) \end{cases}$$

$$\text{variables} = \{X_{100}\}.$$

5. **G3** :  $\begin{cases} \mu_0 : BB(t) \\ \mu_1 : B(t) \end{cases}$   
 $variables = \{X_{100}\}$ .
6. **G4** :  $\begin{cases} \mu_0 : B(t) + \text{hillside}_{0.5,4}(t) \\ \mu_1 : B(t) \end{cases}$   
 $variables = \{X_{47}, \mathbf{X}_{100}\}$ .
7. **G5** :  $\begin{cases} \mu_0 : B(t) + 3\Phi_{1,1}(t) \\ \mu_1 : B(t) \end{cases}$   
 $variables = \{X_1, \mathbf{X}_{48}, X_{100}\}$ .
8. **G6** :  $\begin{cases} \mu_0 : B(t) + 5\Phi_{2,2}(t) \\ \mu_1 : B(t) \end{cases}$   
 $variables = \{X_{48}, \mathbf{X}_{75}, X_{100}\}$ .
9. **G7** :  $\begin{cases} \mu_0 : B(t) + 5\Phi_{3,2}(t) + 5\Phi_{3,4}(t) \\ \mu_1 : B(t) \end{cases}$   
 $variables = \{X_{22}, \mathbf{X}_{35}, X_{49}, X_{74}, \mathbf{X}_{88}, X_{100}\}$ .
10. **G8** :  $\begin{cases} \mu_0 : B(t) + 3\Phi_{2,1.25}(t) + 3\Phi_{2,2}(t) \\ \mu_1 : B(t) \end{cases}$   
 $variables = \{X_9, \mathbf{X}_{35}, X_{48}, X_{62}, \mathbf{X}_{75}, X_{100}\}$ .

2. LOGISTIC-TYPE MODELS CONSIDERED: they are all defined according standard (ii) (see Sec. 4 in the main paper). The process  $X = X(t)$  follows one of the distributions mentioned above and  $Y = \text{Binom}(1, \eta(X))$  with  $\eta(x) = (1 + e^{-\psi(x(t_1), \dots, x(t_k))})^{-1}$ , a function of the relevant variables  $x(t_1), \dots, x(t_k)$ .

- L1**:  $\psi(X) = 10X_{65}$ .
- L2**:  $\psi(X) = 10X_{30} + 10X_{70}$ .
- L3**:  $\psi(X) = 10X_{30} - 10X_{70}$ .
- L4**:  $\psi(X) = 20X_{30} + 50X_{50}20X_{80}$ .
- L5**:  $\psi(X) = 20X_{30} - 50X_{50} + 20X_{80}$ .
- L6**:  $\psi(X) = 10X_{10} + 30X_{40} + 10X_{72} + 10X_{80} + 20X_{95}$ .
- L7**:  $\psi(X) = \sum_{i=1}^{10} 10X_{10i}$ .
- L8**:  $\psi(X) = 20X_{30}^2 + 10X_{50}^4 + 50X_{80}^3$ .
- L9**:  $\psi(X) = 10X_{10} + 10|X_{50}| + 0X_{30}^2X_{85}$ .
- L10**:  $\psi(X) = 20X_{33} + 20|X_{68}|$ .
- L11**:  $\psi(X) = \frac{20}{X_{35}} + \frac{30}{X_{77}}$ .
- L12**:  $\psi(X) = \log X_{35} + \log X_{77}$ .
- L13**:  $\psi(X) = 40X_{20} + 30X_{28} + 20X_{62} + 10X_{67}$ .
- L14**:  $\psi(X) = 40X_{20} + 30X_{28} - 20X_{62} - 10X_{67}$ .
- L15**:  $\psi(X) = 40X_{20} - 30X_{28} + 20X_{62} - 10X_{67}$ .

Some variations of these models have been also considered:

**L3b:**  $\psi(X) = 30X_{30} - 20X_{70}$ .

**L4b:**  $\psi(X) = 30X_{30} + 20X_{50} + 10X_{80}$ .

**L5b:**  $\psi(X) = 10X_{30} - 10X_{50} + 10X_{80}$ .

**L6b:**  $\psi(X) = 20X_{10} + 20X_{40} + 20X_{72} + 20X_{80} + 20X_{95}$ .

**L8b:**  $\psi(X) = 10X_{30}^2 + 10X_{50}^4 + 10X_{80}^3$ .

3. MIXTURE-TYPE MODELS: they are obtained by combining (via mixtures) in several ways the above mentioned Gaussian distributions assumed for  $X|Y = 0$  and  $X|Y = 1$ . These models are denoted M1, ..., M10 in the output tables.

1. **M1** : 
$$\begin{cases} \mu_0 : \begin{cases} B(t) + 3t, & 1/2 \\ B(t) - 2t, & 1/2 \end{cases} \\ \mu_1 : B(t) \end{cases}$$
  
*variables* =  $\{X_{100}\}$ .

2. **M2** : 
$$\begin{cases} \mu_0 : \begin{cases} B(t) + 3\Phi_{2,2}(t), & 1/2 \\ B(t) + 5\Phi_{3,2}(t), & 1/2 \end{cases} \\ \mu_1 : B(t) \end{cases}$$
  
*variables* =  $\{X_{22}, X_{35}, X_{48}, X_{75}, X_{100}\}$ .

3. **M3** : 
$$\begin{cases} \mu_0 : \begin{cases} B(t) + 3\Phi_{2,2}(t), & 1/10 \\ B(t) + 5\Phi_{3,2}(t), & 9/10 \end{cases} \\ \mu_1 : B(t) \end{cases}$$
  
*variables* =  $\{X_{22}, X_{35}, X_{48}, X_{75}, X_{100}\}$ .

4. **M4** : 
$$\begin{cases} \mu_0 : \begin{cases} B(t) + 3\Phi_{2,2}(t), & 1/2 \\ B(t) + 5\Phi_{3,3}(t), & 1/2 \end{cases} \\ \mu_1 : B(t) \end{cases}$$
  
*variables* =  $\{X_{48}, X_{62}, X_{75}, X_{100}\}$ .

5. **M5** : 
$$\begin{cases} \mu_0 : \begin{cases} B(t) + 3\Phi_{2,1}(t), & 1/3 \\ B(t) + 3\Phi_{2,2}(t), & 1/3 \\ B(t) + 5\Phi_{3,2}(t), & 1/3 \end{cases} \\ \mu_1 : B(t) \end{cases}$$
  
*variables* =  $\{X_1, X_{22}, X_{35}, X_{48}, X_{75}, X_{100}\}$ .

6. **M6** : 
$$\begin{cases} \mu_0 : \begin{cases} B(t) + 3\Phi_{2,1}(t), & 1/2 \\ B(t) + 3t, & 1/2 \end{cases} \\ \mu_1 : B(t) \end{cases}$$
  
*variables* =  $\{X_1, X_{22}, X_{49}, X_{100}\}$ .

7. **M7** : 
$$\begin{cases} \mu_0 : \begin{cases} B(t) + 3\Phi_{1,1}(t), & 1/2 \\ BB(t), & 1/2 \end{cases} \\ \mu_1 : B(t) \end{cases}$$
  
*variables* =  $\{X_1, X_{48}, X_{100}\}$ .

8. **M8** : 
$$\begin{cases} \mu_0 : \begin{cases} B(t) + \theta t, \theta \sim N(0, 5), & 1/2 \\ B(t) + \text{hillside}_{0.5,5}(t), & 1/2 \end{cases} \\ \mu_1 : B(t) \end{cases}$$
  
*variables* =  $\{X_{47}, X_{100}\}$ .

9. **M9** : 
$$\begin{cases} \mu_0 : \begin{cases} B(t) + \theta t, \theta \sim N(0, 5), & 1/2 \\ BB(t), & 1/2 \end{cases} \\ \mu_1 : B(t) \end{cases}$$
  
*variables* =  $X_{100}$ .

10. **M10** : 
$$\begin{cases} \mu_0 : \begin{cases} B(t) + 3\Phi_{1,1}(t), & 1/3 \\ B(t) - 3t, & 1/3 \\ BB(t), & 1/3 \end{cases} \\ \mu_1 : B(t) \end{cases}$$
  
*variables* =  $\{X_1, X_{48}, X_{100}\}$ .

11. **M11** : 
$$\begin{cases} \mu_0 : \begin{cases} B(t) + 3\Phi_{1,1}(t), & 1/4 \\ B(t) - 3t, & 1/4 \\ B(t) + \text{hillside}_{0.5,5}(t), & 1/4 \\ BB(t), & 1/4 \end{cases} \\ \mu_1 : B(t) \end{cases}$$
  
*variables* =  $\{X_1, X_{48}, X_{100}\}$ .

Finally, the full list of models involved is as follows:

1. L1 OU	26. L5 OU	51. L9 sB	76. L15 OU
2. L1 OUt	27. L5b OU	52. L9 ssB	77. L15 OUt
3. L1 B	28. L5 OUt	53. L10 OU	78. L15 B
4. L1 sB	29. L5 B	54. L10 B	79. L15 sB
5. L1 ssB	30. L5 sB	55. L10 sB	80. G1
6. L2 OU	31. L5 ssB	56. L10 ssB	81. G1b
7. L2 OUt	32. L6 OU	57. L11 OU	82. G2
8. L2 B	33. L6b OU	58. L11 OUt	83. G2b
9. L2 sB	34. L6 OUt	59. L11 B	84. G3
10. L2 ssB	35. L6b OUt	60. L11 sB	85. G4
11. L3 OU	36. L6 B	61. L11 ssB	86. G5
12. L3b OU	37. L6 sB	62. L12 OU	87. G6
13. L3 OUt	38. L6 ssB	63. L12 OUt	88. G7
14. L3b OUt	39. L7 OU	64. L12 B	89. G8
15. L3 B	40. L7b OU	65. L12 sB	90. M1
16. L3b B	41. L7 OUt	66. L12 ssB	91. M2
17. L3 sB	42. L7b OUt	67. L13 OU	92. M3
18. L3 ssB	43. L7 B	68. L13 OUt	93. M4
19. L4 OU	44. L7 sB	69. L13 B	94. M5
20. L4b OU	45. L7 ssB	70. L13 sB	95. M6
21. L4 OUt	46. L8 B	71. L13 ssB	96. M7
22. L4b OUt	47. L8 sB	72. L14 OU	97. M8
23. L4 B	48. L8 ssB	73. L14 OUt	98. M9
24. L4 sB	49. L8b OU	74. L14 B	99. M10
25. L4 ssB	50. L9 B	75. L14 sB	100. M11

We next provide a few simulation results. See [www.uam.es/antonio.cuevas/exp/mRMR-outputs.xlsx](http://www.uam.es/antonio.cuevas/exp/mRMR-outputs.xlsx) for the full simulation outputs.

NB accuracy outputs						
Model	MID	FCD	RD	VD	CD	Base
L7_OU	90.73	87.01	90.41	87.72	90.50	93.35
L1_OUt	72.54	74.92	74.10	74.56	74.26	73.33
L14_B	75.89	77.31	77.17	76.72	76.75	75.33
L9_sB	84.73	86.01	85.84	85.40	85.78	82.27
G1b	79.74	75.94	80.73	81.66	77.67	79.49
G3	76.22	64.54	78.84	78.78	72.67	71.24
G6	83.13	83.50	84.38	83.96	84.28	74.90
M1	79.12	73.09	80.93	81.89	76.77	77.61
M4	64.73	68.04	67.91	67.48	67.89	61.36
M6	81.25	80.09	83.06	82.45	83.21	78.02

Table 10.- Average NB accuracy (proportion of correct classification) outputs, over 200 runs of the considered methods with sample size  $n = 50$ .

NB number of variables						
Model	MID	FCD	RD	VD	CD	Base
L7_OU	12.1	14.1	10.1	11.5	11.1	100
L1_OUt	8.9	8.0	7.0	5.9	6.6	100
L14_B	7.9	8.0	6.0	7.5	5.9	100
L9_sB	4.9	7.5	4.7	4.9	5.3	100
G1b	6.9	13.4	4.8	1.5	9.0	100
G3	6.4	11.6	3.7	3.7	8.2	100
G6	3.4	1.9	3.5	3.1	2.7	100
M1	4.9	11.7	4.5	1.4	8.4	100
M4	6.5	5.0	5.1	3.4	4.6	100
M6	7.1	7.6	5.5	5.6	6.4	100

Table 11.- Average number of selected variables over 200 runs of the considered methods with sample size  $n = 50$  using NB.

<i>k</i> -NN accuracy outputs						
Model	MID	FCD	RD	VD	CD	Base
L7.OU	90.74	86.89	90.78	87.79	90.67	92.21
L1.OUt	75.83	77.34	76.77	77.22	77.11	75.81
L14.B	75.34	77.16	77.29	76.20	76.49	74.43
L9.sB	86.79	87.39	87.35	87.03	87.28	86.10
G1b	79.11	75.74	80.00	80.01	78.13	78.57
G3	73.39	61.97	77.28	77.03	68.20	65.26
G6	91.95	84.16	88.22	85.80	84.68	92.19
M1	81.63	75.47	82.79	83.00	80.59	80.72
M4	72.94	71.60	74.72	70.30	71.66	73.29
M6	83.08	79.70	84.13	84.26	84.02	80.99

Table 12.- Average *k*-NN accuracy (proportion of correct classification) outputs, over 200 runs of the considered methods with sample size  $n = 50$ .

<i>k</i> -NN number of variables						
Model	MID	FCD	RD	VD	CD	Base
L7.OU	11.5	14.5	10.4	12.1	11.3	100
L1.OUt	9.0	7.9	6.9	6.5	6.8	100
L14.B	8.3	7.6	5.5	8.0	6.5	100
L9.sB	6.3	7.7	6.0	7.1	6.0	100
G1b	7.8	11.7	6.5	6.3	8.7	100
G3	5.1	11.2	2.5	2.9	7.8	100
G6	11.5	12.6	9.0	8.2	7.5	100
M1	7.8	11.4	6.3	4.9	8.6	100
M4	11.7	16.1	10.4	9.7	10.1	100
M6	9.9	9.6	7.5	8.7	7.6	100

Table 13.- Average number of selected variables over 200 runs of the considered methods with sample size  $n = 50$  using *k*-NN.

LDA accuracy outputs						
Model	MID	FCD	RD	VD	CD	Base
L7.OU	89.27	85.13	89.75	86.81	90.10	-
L1.OUt	72.05	73.74	73.48	73.96	73.66	-
L14.B	75.25	76.35	77.12	75.62	76.27	-
L9.sB	84.91	84.88	84.96	84.69	85.12	-
G1b	53.35	52.22	54.15	54.49	51.67	-
G3	52.26	50.91	53.53	53.51	51.06	-
G6	95.28	87.92	90.54	86.59	87.80	-
M1	54.44	53.64	54.88	54.68	53.70	-
M4	78.95	70.98	76.46	71.37	71.30	-
M6	79.92	79.53	80.80	80.57	80.70	-

Table 14.- Average LDA accuracy (proportion of correct classification) outputs, over 200 runs of the considered methods with sample size  $n = 50$ .

**LDA number of variables**

Model	MID	FCD	RD	VD	CD	Base
L7_OU	5.5	6.9	6.2	6.1	7.2	-
L1_OUt	5.6	4.6	4.6	4.4	4.9	-
L14_B	3.6	3.2	3.1	4.1	3.6	-
L9_sB	4.0	3.5	3.3	3.4	3.5	-
G1b	5.6	7.0	5.3	4.6	7.4	-
G3	7.1	8.9	5.0	5.0	8.9	-
G6	10.7	14.3	11.2	7.8	11.6	-
M1	5.5	7.2	5.3	5.7	6.8	-
M4	11.1	10.2	10.3	7.4	8.5	-
M6	6.4	4.5	5.2	5.2	4.8	-

Table 15.- Average number of selected variables over 200 runs of the considered methods with sample size  $n = 50$  using LDA.**SVM accuracy outputs**

Model	MID	FCD	RD	VD	CD	Base
L7_OU	90.73	87.01	90.41	87.72	90.50	93.35
L1_OUt	72.54	74.92	74.10	74.56	74.26	73.33
L14_B	75.89	77.31	77.17	76.72	76.75	75.33
L9_sB	84.73	86.01	85.84	85.40	85.78	82.27
G1b	79.74	75.94	80.73	81.66	77.67	79.49
G3	76.22	64.54	78.84	78.78	72.67	71.24
G6	83.13	83.50	84.38	83.96	84.28	74.90
M1	79.12	73.09	80.93	81.89	76.77	77.61
M4	64.73	68.04	67.91	67.48	67.89	61.36
M6	81.25	80.09	83.06	82.45	83.21	78.02

Table 16.- Average SVM accuracy (proportion of correct classification) outputs, over 200 runs of the considered methods with sample size  $n = 50$ .**SVM number of variables**

Model	MID	FCD	RD	VD	CD	Base
L7_OU	12.1	14.1	10.1	11.5	11.1	100
L1_OUt	8.9	8.0	7.0	5.9	6.6	100
L14_B	7.9	8.0	6.0	7.5	5.9	100
L9_sB	4.9	7.5	4.7	4.9	5.3	100
G1b	6.9	13.4	4.8	1.5	9.0	100
G3	6.4	11.6	3.7	3.7	8.2	100
G6	3.4	1.9	3.5	3.1	2.7	100
M1	4.9	11.7	4.5	1.4	8.4	100
M4	6.5	5.0	5.1	3.4	4.6	100
M6	7.1	7.6	5.5	5.6	6.4	100

Table 17.- Average number of selected variables over 200 runs of the considered methods with sample size  $n = 50$  using SVM.

## 2 Results with quotient criterion and other classifiers

The outputs included in the paper correspond to the difference criterion (in order to combine the relevance and redundancy measures). We provide here some additional results for the quotient criterion, instead of the difference one. Besides, Figure 2 in the paper was produced using only the outputs for the  $k$ -NN classifier. In this document we show the analogous displays for LDA, SVM and NB. Again, the entire simulation outputs can be downloaded from [www.uam.es/antonio.cuevas/exp/mRMR-outputs.xlsx](http://www.uam.es/antonio.cuevas/exp/mRMR-outputs.xlsx).

Tables 1a-9a below correspond and Tables 1-9 in the main paper with the difference criterion replaced with the quotient one. Figures 2a, 2b and 2c correspond to Figure 2 using the other classifiers.

Output (NB)	Sample size	MIQ	FCQ	RQ	VQ	CQ	Base
Average accuracy	$n = 30$	78.10	78.76	79.53	79.58	79.12	77.28
	$n = 50$	79.59	79.73	80.86	80.81	80.26	78.29
	$n = 100$	80.62	80.54	81.82	81.75	81.16	78.84
	$n = 200$	81.24	81.03	82.48	82.35	81.77	79.13
Average dim. red	$n = 30$	8.9	8.6	7.2	7.0	7.9	100
	$n = 50$	8.3	8.1	6.7	6.7	7.4	100
	$n = 100$	7.7	7.2	6.1	6.1	6.9	100
	$n = 200$	7.1	6.7	5.7	5.9	6.5	100
Victories over Base	$n = 30$	60	65	72	76	68	-
	$n = 50$	67	61	79	78	68	-
	$n = 100$	71	64	88	86	79	-
	$n = 200$	75	68	92	91	84	-

Table 1a.- Performance outputs for the considered methods, using NB and the quotient criterion, with different sample sizes. Each output is the result of the 100 different models for each sample size.

Output ( $k$ -NN)	Sample size	MIQ	FCQ	RQ	VQ	CQ	Base
Average accuracy	$n = 30$	80.02	79.65	80.85	80.82	80.09	78.98
	$n = 50$	81.32	80.40	81.72	81.67	80.87	80.34
	$n = 100$	82.84	81.34	82.73	82.65	81.83	81.99
	$n = 200$	84.06	82.09	83.56	83.49	82.65	83.38
Average dim. red	$n = 30$	9.3	9.5	7.4	7.6	8.1	100
	$n = 50$	9.6	9.6	7.6	7.8	8.3	100
	$n = 100$	9.9	9.9	8.0	8.2	8.6	100
	$n = 200$	10.1	10.1	8.3	8.5	9.0	100
Victories over Base	$n = 30$	71	58	76	74	67	-
	$n = 50$	67	53	73	72	64	-
	$n = 100$	71	49	64	64	55	-
	$n = 200$	64	42	62	64	54	-

Table 2a.- Performance outputs for the considered methods, using  $k$ -NN and the quotient criterion, with different sample sizes. Each output is the result of the 100 different models for each sample size.



Output (LDA)	Sample size	MIQ	FCQ	RQ	VQ	CQ	Base
Average accuracy	$n = 30$	78.67	77.58	78.64	78.64	78.15	60.80
	$n = 50$	80.20	78.53	79.58	79.52	79.11	58.75
	$n = 100$	81.74	79.62	80.65	80.52	80.25	53.11
	$n = 200$	82.90	80.47	81.53	81.35	81.10	73.25
Average dim. red	$n = 30$	5.8	4.7	4.7	4.7	5.1	100
	$n = 50$	6.9	5.7	5.6	5.6	6.0	100
	$n = 100$	8.3	7.1	6.9	7.0	7.3	100
	$n = 200$	9.5	8.3	8.0	8.1	8.4	100

Table 3a.- Performance outputs for the considered methods, using LDA and the quotient criterion, with different sample sizes. Each output is the result of the 100 different models for each sample size.

Output (SVM)	Sample size	MIQ	FCQ	RQ	VQ	CQ	Base
Average accuracy	$n = 30$	81.62	79.81	80.69	80.65	80.27	81.91
	$n = 50$	82.69	80.42	81.43	81.35	80.96	82.99
	$n = 100$	83.80	81.21	82.20	82.12	81.76	84.11
	$n = 200$	84.61	81.79	82.90	82.76	82.42	84.91
Average dim. red	$n = 30$	10.6	10.3	9.1	9.2	9.5	100
	$n = 50$	10.7	10.4	9.3	9.4	9.7	100
	$n = 100$	11.1	10.5	9.5	9.7	9.9	100
	$n = 200$	11.4	10.7	9.7	9.9	10.0	100
Victories over Base	$n = 30$	32	37	49	47	42	-
	$n = 50$	35	34	51	52	44	-
	$n = 100$	35	33	51	50	48	-
	$n = 200$	33	31	52	51	48	-

Table 4a.- Performance outputs for the considered methods, using SVM and the quotient criterion, with different sample sizes. Each output is the result of the 100 different models for each sample size.

Ranking criterion (NB)	Sample size	MIQ	FCQ	RQ	VQ	CQ
Relative	$n = 30$	2.27	5.67	8.69	8.63	7.65
	$n = 50$	2.69	4.94	9.09	8.70	7.51
	$n = 100$	2.75	4.75	9.21	8.80	7.44
	$n = 200$	2.71	4.57	8.87	8.31	7.41
Positional	$n = 30$	6.78	7.83	8.53	8.50	8.39
	$n = 50$	6.79	7.57	8.93	8.51	8.22
	$n = 100$	6.80	7.47	9.01	8.58	8.14
	$n = 200$	6.84	7.56	8.92	8.43	8.25
F1	$n = 30$	12.25	15.85	17.39	17.58	17.01
	$n = 50$	12.24	14.90	19.19	17.37	16.35
	$n = 100$	12.35	14.60	19.67	17.38	16
	$n = 200$	12.49	14.92	19.28	16.86	16.45

Table 5a.- Global scores of the considered (quotient-based) methods using three different ranking criteria with the NB classifier.

Ranking criterion ( $k$ -NN)	Sample size	MIQ	FCQ	RQ	VQ	CQ
Relative	$n = 30$	3.70	3.97	8.51	8.09	6.03
	$n = 50$	4.39	3.72	7.84	7.59	5.61
	$n = 100$	4.93	3.46	7.24	6.91	5.15
	$n = 200$	5.52	3.00	6.72	6.52	5.00
Positional	$n = 30$	7.31	7.29	9.06	8.64	7.70
	$n = 50$	7.55	7.30	8.90	8.67	7.58
	$n = 100$	7.75	7.37	8.82	8.62	7.49
	$n = 200$	7.96	7.43	8.56	8.45	7.60
F1	$n = 30$	14.32	13.96	19.66	17.80	14.26
	$n = 50$	15.27	14.06	18.78	17.94	13.95
	$n = 100$	16.02	14.19	18.44	17.90	13.62
	$n = 200$	16.84	14.09	17.48	17.57	14.02

Table 6a.- Global scores of the considered (quotient-based) methods using three different ranking criteria with the  $k$ -NN classifier.

Ranking criterion (LDA)	Sample size	MIQ	FCQ	RQ	VQ	CQ
Relative	$n = 30$	3.94	3.14	7.48	7.38	5.38
	$n = 50$	4.26	2.86	6.97	6.66	5.19
	$n = 100$	4.76	2.60	6.98	6.43	5.33
	$n = 200$	5.27	2.36	6.78	6.13	5.23
Positional	$n = 30$	7.49	6.99	9.01	8.96	7.55
	$n = 50$	7.64	7.12	8.90	8.64	7.70
	$n = 100$	7.72	7.13	8.89	8.52	7.74
	$n = 200$	7.80	7.23	8.79	8.36	7.82
F1	$n = 30$	15.05	12.67	19.11	19.32	13.85
	$n = 50$	15.63	12.95	18.91	18.07	14.44
	$n = 100$	15.80	13.04	18.83	17.72	14.61
	$n = 200$	16.25	13.29	18.62	17.04	14.80

Table 7a.- Global scores of the considered (quotient-based) methods using three different ranking criteria with LDA.

Ranking criterion (SVM)	Sample size	MIQ	FCQ	RQ	VQ	CQ
Relative	$n = 30$	6.02	2.85	6.58	6.28	4.42
	$n = 50$	5.99	2.72	6.70	6.15	4.73
	$n = 100$	6.14	2.61	6.43	5.99	4.66
	$n = 200$	6.42	2.30	6.29	5.75	4.68
Positional	$n = 30$	8.26	7.20	8.74	8.46	7.34
	$n = 50$	8.16	7.19	8.80	8.43	7.42
	$n = 100$	8.26	7.31	8.66	8.32	7.48
	$n = 200$	8.28	7.36	8.61	8.22	7.56
F1	$n = 30$	17.90	13.78	17.99	17.17	13.16
	$n = 50$	17.58	13.51	18.21	17.28	13.42
	$n = 100$	17.97	13.86	17.71	16.95	13.59
	$n = 200$	17.89	13.85	17.70	16.58	14.06

Table 8a.- Global scores of the considered (quotient-based) methods using three different ranking criteria with the linear SVM.

<b>NB outputs</b>							
Output	Data	MIQ	FCQ	RQ	VQ	CQ	Base
Classification accuracy	Growth	88.17	87.10	86.02	86.02	87.10	84.95
	Tecator	96.28	97.67	99.53	99.53	98.14	97.21
	Phoneme	73.08	80.20	80.38	80.15	80.32	74.08
Number of variables	Growth	1.5	1.1	1.1	1.1	1.1	31
	Tecator	4.8	5.0	1.0	1.0	4.4	100
	Phoneme	14.5	10.6	16.7	16.8	14.1	256

<b>k-NN outputs</b>							
Output	Data	MIQ	FCQ	RQ	VQ	CQ	Base
Classification accuracy	Growth	95.70	83.87	83.87	83.87	83.87	96.77
	Tecator	96.74	99.07	99.53	99.53	98.60	98.60
	Phoneme	75.53	81.42	79.79	80.38	80.61	78.80
Number of variables	Growth	3.9	1.0	1.0	1.0	1.0	31
	Tecator	4.0	3.0	1.0	1.0	4.3	100
	Phoneme	18.4	12.1	12.3	15.2	6.7	256

<b>LDA outputs</b>							
Output	Data	MIQ	FCQ	RQ	VQ	CQ	Base
Classification accuracy	Growth	95.70	91.40	91.40	91.40	91.40	-
	Tecator	94.88	94.42	94.88	94.42	95.35	-
	Phoneme	74.55	78.88	79.10	79.63	80.26	-
Number of variables	Growth	3.7	5.0	4.9	4.9	5.0	-
	Tecator	6.1	8.4	4.1	2.2	3.1	-
	Phoneme	19.0	8.9	10.0	9.0	9.2	-

<b>SVM outputs</b>							
Output	Data	MIQ	FCQ	RQ	VQ	CQ	Base
Classification accuracy	Growth	94.62	87.10	87.10	87.10	86.02	95.70
	Tecator	98.14	99.07	99.53	99.07	98.60	99.07
	Phoneme	75.30	80.71	80.67	80.37	80.33	80.96
Number of variables	Growth	3.5	5.0	4.9	4.9	5.0	31
	Tecator	6.7	2.1	1.0	1.0	4.1	100
	Phoneme	19.3	10.1	11.3	10.8	12.2	256

Table 9a.- Performances of the different (quotient-based) mRMR methods in three real data sets. From top to bottom tables stand for Naive Bayes,  $k$ -NN, LDA and linear SVM outputs respectively.

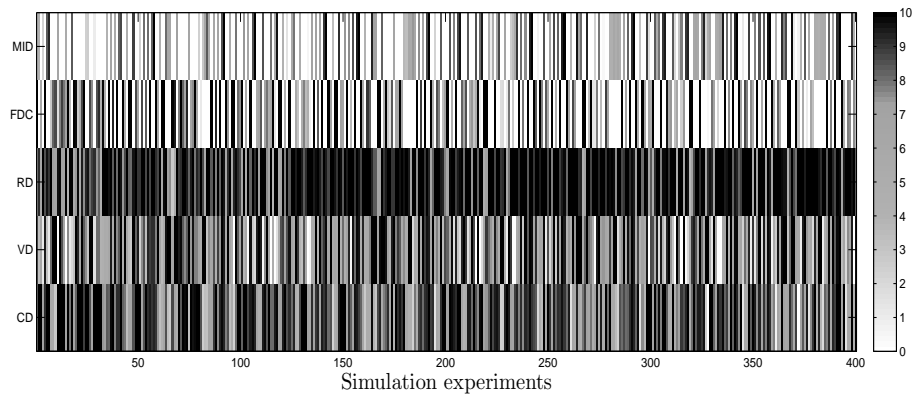


Figure 2a.- Cromatic version of the global relative ranking table taking into account the 400 considered experiments (columns) and the Naive Bayes classifier.

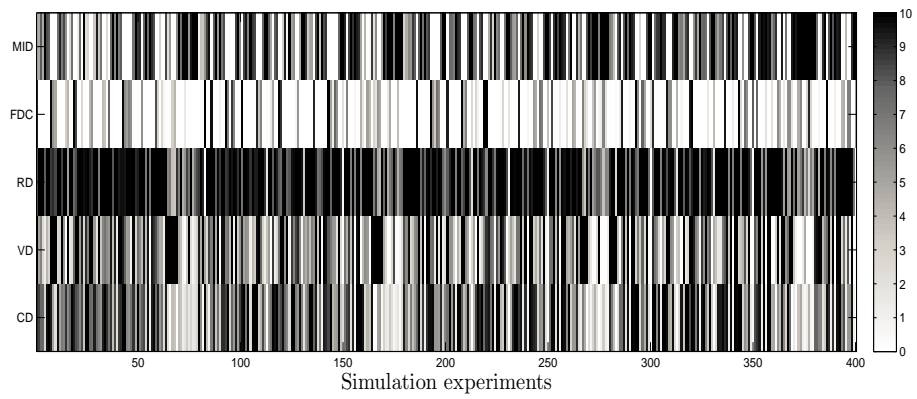


Figure 2b.- Cromatic version of the global relative ranking table taking into account the 400 considered experiments (columns) and the Linear Discriminant Analysis.

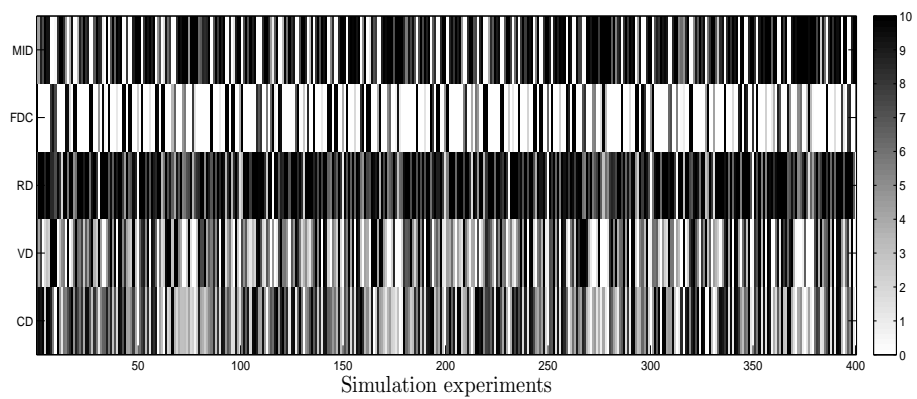


Figure 2c.- Cromatic version of the global relative ranking table taking into account the 400 considered experiments (columns) and the linear SVM.