

Algorithmic Modeling of Spectroscopic Data to Quantify Binary Mixtures of Vinegars from Different Botanical Origins

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Supplementary material

Additional information regarding different optimization procedures followed is detailed in the following sections.

MLR-based models

In Tables S1 1-6 the fit coefficients of five vinegars for each kind of binary blend (six binary possible mixtures) are shown. These coefficients are the result of averaging the ones obtained from the k-fold cross-validation analysis (k=6).

Table SI.1. Values of the fit coefficients of the MLRs designed to estimate the composition of white wine vinegar blends.

Term	Red Wine	Cider	Apple	Molasses	Rice
Constant	-0.03	0.01	-0.01	0.83	-0.02
AUC₁	-39.87	-1.98	4.53	12.65	-0.88
AUC₂	35.64	3.55	-8.45	-16.36	7.38
AUC₃	35.86	-0.17	4.48	-9.58	-4.99
AUC₄	-118.93	-1.49	0.45	14.87	-3.07
AUC₅	166.28	2.06	-1.65	-11.39	2.18
AUC₆	-96.98	-5.02	0.35	21.04	-10.95
AUC₇	29.65	-3.17	-6.33	-21.42	-0.93
AUC₈	75.39	7.12	12.22	42.14	40.69
AUC₉	-193.56	4.56	-8.41	-36.28	-23.16
AUC₁₀	211.35	-7.04	4.23	34.28	-16.91
AUC₁₁	-80.62	4.28	1.09	-35.45	14.12
AUC₁₂	-121.83	-3.28	-6.84	-22.74	-22.05
AUC₁₃	170.87	0.28	2.14	26.53	12.46
AUC₁₄	-64.83	2.47	-4.26	-34.85	0.28
AUC₁₅	-4.73	-1.89	6.93	37.30	7.39

Table SI.2. Values of the fit coefficients of the MLRs designed to estimate the composition of red wine vinegar blends.

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Term	White Wine	Cider	Apple	Molasses	Rice
Constant	-0.10	-0.02	0.02	1.09	0.02
AUC₁	-40.07	-1.90	1.91	10.03	-3.87
AUC₂	104.90	2.79	-6.11	-24.57	2.18
AUC₃	-24.34	-0.16	9.48	14.51	3.87
AUC₄	-114.71	-0.70	-5.59	11.46	-5.42
AUC₅	160.27	2.92	-12.01	-58.74	-6.40
AUC₆	-159.24	-7.11	15.00	53.45	13.15
AUC₇	35.26	-0.13	11.96	55.38	11.87
AUC₈	47.04	5.55	-13.88	-35.45	0.97
AUC₉	-49.99	4.90	-11.71	-53.58	-12.06
AUC₁₀	96.32	-10.24	20.26	67.59	-9.34
AUC₁₁	-129.39	7.22	-13.10	-60.23	2.37
AUC₁₂	186.08	-3.91	7.93	15.08	-3.24
AUC₁₃	-208.07	1.60	-10.46	-2.87	-0.63
AUC₁₄	118.92	0.79	5.84	-15.00	9.21
AUC₁₅	-22.87	-1.59	0.37	21.72	-2.59

Table SI.3. Values of the fit coefficients of the MLRs designed to estimate the composition of apple cider vinegar blends.

Term	White Wine	Red Wine	Apple	Molasses	Rice
Constant	0.10	0.00	-0.08	0.92	-0.02
AUC₁	-1.25	-0.40	-13.95	-0.09	-3.10
AUC₂	24.67	0.79	-4.00	-9.10	-6.86
AUC₃	-51.72	-1.79	-22.15	24.69	16.27
AUC₄	-8.32	1.30	43.23	8.90	7.13
AUC₅	93.50	1.51	-3.09	-71.16	-24.01
AUC₆	-62.62	-0.66	-1.05	64.24	3.56
AUC₇	25.14	0.91	144.52	-28.47	6.77
AUC₈	-43.83	-5.25	-150.32	15.46	16.06
AUC₉	26.75	0.86	-28.68	-18.79	-0.23
AUC₁₀	-45.23	6.22	67.86	57.56	-23.30
AUC₁₁	102.57	-7.18	-25.40	-90.86	0.48
AUC₁₂	-131.07	5.29	-51.48	99.66	17.18
AUC₁₃	151.02	1.60	85.22	-105.71	-28.45
AUC₁₄	-77.93	-3.34	-39.28	45.78	24.87
AUC₁₅	-4.00	0.78	-9.71	6.10	-4.16

Table SI.4. Values of the fit coefficients of the MLRs designed to estimate the composition of apple vinegar blends.

Term	White Wine	Red Wine	Cider	Molasses	Rice
Constant	0.67	0.03	0.43	0.46	-0.05

AUC₁	-21.27	1.04	-19.45	12.80	3.67
AUC₂	37.73	-2.27	43.73	-20.04	-6.18
AUC₃	-60.38	0.05	-45.68	41.04	6.07
AUC₄	77.85	-0.06	27.49	-55.35	-10.69
AUC₅	-0.47	-0.09	7.78	-5.67	-0.44
AUC₆	-63.47	7.60	-63.82	50.97	13.81
AUC₇	21.60	-4.90	60.97	-13.34	-3.56
AUC₈	22.70	-4.34	136.20	-48.34	17.01
AUC₉	-42.33	1.34	-214.26	59.68	-11.07
AUC₁₀	7.84	5.28	54.42	0.64	-15.56
AUC₁₁	80.89	-6.97	44.58	-75.75	2.57
AUC₁₂	-140.96	5.43	-102.58	132.05	0.18
AUC₁₃	171.55	1.53	138.64	-152.14	-9.82
AUC₁₄	-88.42	-3.43	-105.94	70.60	15.17
AUC₁₅	-3.00	0.62	40.99	1.13	-0.63

Table SI.5. Values of the fit coefficients of the MLRs designed to estimate the composition of molasses vinegar blends.

Term	White Wine	Red Wine	Cider	Apple	Rice
Constant	-0.09	-0.02	0.05	0.01	0.08
AUC₁	-10.31	0.42	-0.82	3.13	-1.38
AUC₂	19.71	-1.30	1.00	-8.31	3.93
AUC₃	-15.83	1.88	0.64	8.53	-3.62
AUC₄	13.86	-1.26	-0.57	-4.37	1.19
AUC₅	6.04	-1.88	-1.37	-2.30	0.43
AUC₆	1.89	6.22	-6.35	3.80	-13.72
AUC₇	-65.31	-3.55	12.69	7.08	24.10
AUC₈	44.69	-8.78	4.23	-9.40	5.65
AUC₉	-13.96	7.87	-15.31	3.76	-6.34
AUC₁₀	-19.53	1.88	11.40	-3.79	-11.08
AUC₁₁	94.04	-1.75	2.17	-5.62	-5.91
AUC₁₂	-118.36	-5.33	-24.84	25.58	9.07
AUC₁₃	137.71	11.95	26.27	-31.85	-19.66
AUC₁₄	-60.48	-8.06	-8.85	11.63	20.17
AUC₁₅	-16.38	2.05	0.17	1.76	-0.79

Table SI.6. Values of the fit coefficients of the MLRs designed to estimate the composition of rice vinegar blends.

Term	White Wine	Red Wine	Cider	Apple	Molasses
Constant	-0.18	-0.04	0.06	-0.05	0.81
AUC₁	13.13	1.13	0.57	4.31	-7.09
AUC₂	-11.52	-0.59	-2.44	-8.34	18.61

AUC₃	-46.51	-2.75	0.85	12.63	11.48
AUC₄	63.28	2.55	2.95	-16.56	-42.72
AUC₅	39.65	2.13	-3.06	5.02	-4.77
AUC₆	-83.16	-2.20	-3.26	7.67	39.38
AUC₇	32.57	0.20	8.73	-12.15	-13.30
AUC₈	-137.62	-9.60	1.89	24.22	27.29
AUC₉	199.98	10.92	-1.60	-36.23	-57.19
AUC₁₀	-93.28	0.65	-7.40	26.90	54.25
AUC₁₁	19.17	-6.90	5.80	-6.50	-29.85
AUC₁₂	78.97	9.30	-3.57	-8.65	-28.48
AUC₁₃	-97.17	-4.49	2.72	6.87	36.20
AUC₁₄	62.00	0.00	-1.06	-3.10	-30.96
AUC₁₅	-36.01	0.56	-0.44	2.98	24.10

Optimization process: training function and MLP parameters

The optimization of an MLP comprises more than the modification of the value of the weights. There are several elements that must be also considered, such as the training function selected, the hidden neuron number (HNN), and the learning coefficients.

The training function controls the training process. It is an algorithm responsible of the modification of the value of the weights during the training phase [Demuth *et al.* 2007]. Despite of the existence of several of these functions, in the case considered the different MLPs constructed employed trainLM, as it is considered the fastest training function due to its memory reduction feature which is used when the computational requirements are huge. In addition, it presents a compromise between conjugate gradient and quasi-Newtonian methods in the learning process [Parmar *et al.* 2011, Demuth *et al.* 2007].

On the other hand, the HNN was optimized following a heuristic method based on several trial-and-error test, and choosing the one that offers the best results, in terms of low error and high R^2 value. Due to the traits of the systems studied (15 input nodes, five output neurons, and 105 samples per binary blend), the range considered was from two to five neurons, so the number of weights was always below the number of data instances that were available. It must be mentioned, that during this optimization, the learning coefficients were maintained constant ($L_c = 0.001$; $L_d = 0.1$; $L_i = 10$). The results are shown in **Table SI.7** to **Table SI.12**.

Table SI.7. Statistical results attained in the HNN optimization process for the white wine vinegar blends, in terms of R^2 and MAE. The best HNN appears in bold.

HNN	R^2					MAE (% v/v)				
	Red Wine	Cider	Apple	Molasses	Rice	Red Wine	Cider	Apple	Molasses	Rice

2	0.99	0.96	0.94	0.96	0.98	1.2	2.6	1.0	1.9	2.2
3	0.98	0.99	0.99	>0.99	0.99	0.7	1.0	0.4	0.2	1.2
4	0.98	0.92	0.98	0.99	>0.99	0.8	3.1	1.0	1.3	1.1
5	0.98	>0.99	>0.99	0.99	>0.99	1.1	0.5	0.1	0.5	0.8

Table SI.8. Statistical results attained in the HNN optimization process for the red wine vinegar blends, in terms of R^2 and MAE. The best HNN appears in bold.

HNN	R^2					MAE (% v/v)				
	White Wine	Cider	Apple	Molasses	Rice	White Wine	Cider	Apple	Molasses	Rice
2	0.97	0.99	0.98	0.97	>0.99	3.0	2.2	1.9	3.5	1.6
3	0.99	0.98	>0.99	0.99	>0.99	1.8	2.3	0.5	2.4	1.8
4	0.98	>0.99	>0.99	0.99	>0.99	2.7	0.7	0.2	1.8	0.5
5	0.99	>0.99	>0.99	0.99	>0.99	2.2	1.3	0.5	1.4	1.3

Table SI.9. Statistical results attained in the HNN optimization process for the apple cider vinegar blends, in terms of R^2 and MAE. The best HNN appears in bold.

HNN	R^2					MAE (% v/v)				
	White Wine	Red wine	Apple	Molasses	Rice	White Wine	Red wine	Apple	Molasses	Rice
2	0.68	0.99	0.96	0.85	0.96	7.9	1.1	2.8	2.0	2.5
3	0.49	0.98	0.68	0.95	0.98	10.2	1.8	5.8	1.6	1.6
4	0.97	0.99	0.88	0.84	>0.99	2.5	1.1	4.1	2.7	1.1
5	0.98	0.98	0.99	0.93	0.99	2.6	1.3	1.1	0.9	1.2

Table SI.10. Statistical results attained in the HNN optimization process for the apple vinegar blends, in terms of R^2 and MAE. The best HNN appears in bold.

HNN	R^2					MAE (% v/v)				
	White Wine	Red wine	Cider	Molasses	Rice	White Wine	Red wine	Cider	Molasses	Rice
2	0.99	0.99	0.97	>0.99	0.90	2.5	0.8	2.0	1.1	4.4
3	0.99	0.99	0.86	0.96	0.97	1.2	0.5	2.4	4.0	1.8
4	>0.99	>0.99	0.98	0.99	>0.99	1.5	0.4	1.2	1.8	0.6
5	>0.99	>0.99	0.97	0.99	0.99	1.2	0.2	1.6	1.6	1.2

Table SI.11. Statistical results attained in the HNN optimization process for the molasses vinegar blends, in terms of R^2 and MAE. The best HNN appears in bold.

HNN	R^2					MAE (% v/v)				
	White Wine	Red wine	Cider	Apple	Rice	White Wine	Red wine	Cider	Apple	Rice
2	>0.99	0.99	>0.99	0.97	0.99	1.3	1.0	1.1	1.7	1.7
3	>0.99	0.99	>0.99	0.97	0.99	1.9	1.7	1.5	2.4	2.6

4	>0.99	0.99	>0.99	0.99	>0.99	0.4	0.9	0.1	0.8	0.4
5	>0.99	0.99	>0.99	0.99	0.99	1.1	1.1	0.2	0.9	1.5

Table SI.12. Statistical results attained in the HNN optimization process for the rice vinegar blends, in terms of R^2 and MAE. The best HNN appears in bold.

HNN	R^2					MAE (% v/v)				
	White Wine	Red wine	Cider	Apple	Molasses	White Wine	Red wine	Cider	Apple	Molasses
2	0.98	0.95	0.99	0.98	0.68	1.6	1.1	2.1	1.4	2.9
3	0.99	>0.99	>0.99	>0.99	0.99	1.4	0.2	0.7	0.9	1.2
4	0.99	0.98	>0.99	0.99	0.99	1.2	1.1	1.3	1.9	1.1
5	0.99	>0.99	>0.99	>0.99	0.99	1.2	0.3	0.6	0.7	1.0

The optimal HNN was always four or five. In every case, the number of weights was below the number of data instances (76% and 95%, when four and five neurons are used, respectively). When the performance is similar, the combination with the less HNNs must be selected, as the computational requirements of such model will be smaller.

The three parameters regarding the learning coefficient (Lc, Lcd and Lci) were optimized through a Box-Wilson Central Composite design 2^3 + star points experimental design. The ranges tested were from 0.001 to 1 in the case of Lc and Lcd, and from 2 to 100, for Lci. The studied responses were the R^2 and the estimation error, in terms of MAE. During this optimization, the HNN was set to the optimal value determined during the previous analysis for each binary mixture. The results can be seen in the Results and discussion section of the main article.

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