Sweetness power QSARs by PRECLAV software

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> Dedicated to Professor Alexandru T. Balaban on his 75th birthday (received 18 Mar 05; accepted 08 Jun 05; published on the web 30 Jun 05)

Abstract

This paper presents some QSAR (*Quantitative Structure Activity Relationship*) studies with a testing set, realized by the PRECLAV (*Property Evaluation by Class Variables*) computer program. The database we used contains sweeteners with very diverse structures – sugars, halosugars, guanidine derivatives and 3-aminosuccinamic acid derivatives. According to their estimated values of Log(RS), the testing set molecules are classified as "recommended", "uncertain", or "un-recommended" for synthesis. Comparing the estimated Log(RS) values with the observed values we have found that the aforementioned classification is sufficiently correct to have actual practical value, even if the training/testing set contains sweeteners of several different classes. The N-phenyl-guanidine-acetic acid derivatives, with a polycyclic system bonded with the nitrogen atom, represent a distinct subclass of guanidinic sweeteners.

Keywords: QSAR, PRECLAV, sweeteners

Introduction

The PRECLAV (*Property Evaluation by Class Variables*) computer program³² has been used for several years in doing QSAR (*Quantitative Structure Activity Relationship*) studies for "academic" purposes (to test the quality of certain algorithms and/or the predicting ability of certain descriptors) as well as to solve "practical" problems that have been proposed by various research groups in the drug design area (identifying the predictors having the highest influence on the values of the dependent property, and estimating the value of the desired property for molecules not yet synthesized)¹⁻¹¹.

We have recently thoroughly described the program's latest version algorithm.¹²

The present paper presents the results of some QSAR studies in which we have used databases containing sweeteners with a very diverse structure – sugars, halosugars, guanidine derivatives and dipeptides.

Methods and formulae

The molecules have been constructed virtually using the molecular mechanics program, PCMODEL¹³.

The geometry of the minimum energy conformer was obtained by using the MMX force field and GMMX algorithm¹⁴. Further, the geometry was more rigorously optimized with the quantum mechanics program MOPAC¹⁵, using the keyword string: "am1 pulay gnorm=0.01 shift=50 geo-ok mmok camp-king bonds vectors".

The *output* files created by MOPAC for each analyzed molecule are *input* files for PRECLAV and they contain the values of some descriptors. Using the data from the files generated by MOPAC, PRECLAV has computed most of the descriptors and has performed the statistical analysis. A detailed list of descriptors is available as supplementary material.

The analyzed dependent property was Log(RS), where RS (*relative sweetness*) is the sweetness power relative to sucrose. When the analyzed molecules had a common skeleton we used "whole molecule" and "grid" descriptors. Otherwise we used only "whole molecule" descriptors.

The QSAR studies can be made with or without a testing set. In the case of QSAR studies with a testing set, PRECLAV uses the Class function for identifying the significant descriptors. The QSAR equation that PRECLAV uses for prediction purposes in such situations is not the same as the equation one obtains when the program works without a testing set.

The "significant" descriptors satisfy conditions (1) and (2):

$$C_{\nu} > 3 \tag{1}$$

$$Q > 1 \tag{2}$$

where C_v is the coefficient of variation for descriptor values, defined as usual by

$$C_{v} = 100 \, x \, \sigma \,/ \, V_{m} \tag{3}$$

where σ is the standard deviation around the average value, V_m is the average absolute value, and Q is the quality function for the analysed descriptor

$$Q = r^2 / [1 - C^a (1 - b x r^2_{min})]$$
(4)

where r^2 is the square of the Pearson linear correlation between the descriptor values and the dependent property values, r^2_{min} is the minimum value imposed for r^2 ; the default value for r^2_{min} ,

empirically established, is 4 / N (where N is the number of molecules from the training set); the user may modify this value, and C is Class function

$$C = \sigma_N / \sigma_{N+K} \text{ if } \sigma_N < \sigma_{N+K}$$

$$C = \sigma_{N+K} / \sigma_N \text{ if } \sigma_N >= \sigma_{N+K}$$
(5a)
(5b)

where σ_N is σ from formula (3) computed for N molecules from the training set, σ_{N+K} is σ from formula (3) computed for the entire database (N molecules from the training set + K molecules from the testing set), *a* is a real number, whose value is established empirically (*a* = 10) by analysing a large number of databases (training set + testing set), and *b* =1 for the "whole molecule" descriptors and *b* = 2 for the "grid" descriptors (this way the "grid" descriptors selection is more drastic)

It is considered that the Class function measures how representative a sample – from the statistical point of view - is the training set in the joint set of the testing and training sets from the analyzed descriptor's point of view. If the testing set is missing then C = 1 for all descriptors and the condition (4) becomes $r^2 > b \ge r^2_{min}$.

Usually, according to the selection criteria (1) and (2), only 5–25% of the computed descriptors are "significant".

The results of some QSAR studies performed without a testing set, using the same databases we have used here, will be presented in a future paper. Here we present only the results of several QSAR studied performed with a testing set. The training and testing sets have been defined by a standard procedure. This procedure involves the ordering of the molecules in the database according to the value of the dependent property, starting with the smallest value. The molecules with rank 3, 8, 13, 18, 23 ... in the string will form the actual testing set.

The analysis of the training set molecules has produced tens of thousands of multi-linear QSAR equations of the following form:

$$Log(RS) = c_0 + \sum c_k \cdot p_k \tag{6}$$

The "best" QSAR equation was selected according to the value of a cross-validation quality function, specific to PRECLAV¹². This equation was then utilized for predicting the values of Log(RS) for the molecules in the testing set. Once the computations were over, the testing set molecules were classified in three categories: "recommended for synthesis", "uncertain", and "un-recommended for synthesis". The classification was based on Log(RS)'s estimated value, relative to the other estimated values for the rest of the molecules in the testing set. After computing the values of the dependent property for the molecules in the testing set, PRECLAV sorts these molecules according to the estimated values. An average value P_{calc}^{m} is computed for the average.

The program considers "high" the value fulfilling the criterion (7) and "low" the value fulfilling the criterion (8):

$$P_{calc} > P_{calc}^{m} + 0.5 x \sigma$$

$$P_{calc} < P_{calc}^{m} - 0.5 x \sigma$$
(7)
(8)

If the user wishes to synthesize molecules with a pronounced biochemical activity, the molecules fulfilling criterion (7) are "recommended for synthesis", while the ones fulfilling criterion (8) are "un-recommended for synthesis".

In the "practical" QSAR studies, the testing set contains new molecules, not yet synthesized, with a structure imagined by the program user. In this case the observed values of Log(RS) for the testing set are not known because the molecules have not yet been analyzed by physical / chemical methods. It is very important that the program properly sorts the testing set molecules by the estimated values of Log(RS), even if the values themselves do not correspond too well with the real values – the most important thing is that the program arranges the molecules in the correct order. This way the molecules "recommended for synthesis" can be correctly identified. Thus, in the "academic" QSAR studies we present here, we have considered that an adequate measure for the quality of the prediction is the value of the Kendall rank correlation between the computed and the observed values of Log(RS).

The SMILES notation of analysed molecules is available as supplementary material.

Results and Discussion

QSAR study #1

Database: sugars and halosugars, 41 molecules (Fig. 1, Table 1) Dependent property: Log(RS), the values are taken from literature^{16, 17} Training set: 33 molecules (Table 1, normal font) Testing set: 8 molecules (Table 1, bold font) Descriptors: "whole molecule" + "grid" Number of significant descriptors: 99

The type (6) QSAR equation for prediction:

- $c_0 = .0019$
- $c_1 = .7241$
- p₁ QSAR of molecular orbital energies
- $c_2 = -1.8699$
- p₂ A121 (electrostatic attraction force, "grid" descriptor)
- $c_3 = -104.4192$
- p₃ F100 (electrostatic resultant force, "grid" descriptor)

Standard error (training set): 0.338 Fisher F function (training set): 139.9 Kendall cross-validated rank correlation K_{CV} (training set) = 0.8788 Kendall rank correlation K (testing set): 0.7143 Standard error (testing set): 0.489

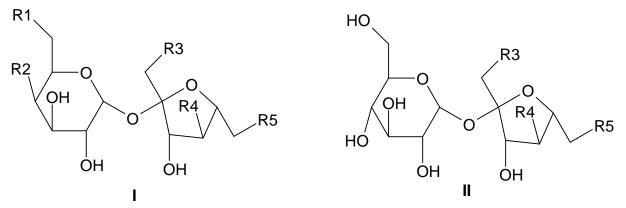


Figure 1. Structure of sugars/halosugars.

The three molecules in the testing set having the smallest observed values of Log(RS) have been labeled "un-recommended for synthesis". Two molecules having the highest observed values of Log(RS) have been labeled "recommended for synthesis" and another one has been labeled "uncertain". In case of molecule **23** the value of Log(RS) is over-estimated, while for molecule **33** the value of Log(RS) is under-estimated.

Crt. No.	Name	Str. in Fig. 1	\mathbf{R}_1	R_2	R ₃	R_4	R_5	Log RS Obs.	Log RS Calc.	Recommended for synthesis
1	Lactose	_	-	-	-	-	-	-0.699	-0.151	*
2	-	Ι	OH	OH	OH	OH	OH	-0.699	-0.174	
3	Mannose	-	-	-	-	-	-	-0.523	-0.081	no
4	Galactose	-	-	-	-	-	-	-0.495	-0.819	
5	Maltose	-	-	-	-	-	-	-0.481	0.250	
6	Xylose	-	-	-	-	-	-	-0.398	-0.204	
7	α-Glucose	-	-	-	-	-	-	-0.155	-0.478	
8	β-Glucose	-	-	-	-	-	-	-0.097	-0.523	no
9	Sorbose	-	-	-	-	-	-	-0.066	0.242	
10	-	Ι	OH	Н	OH	OH	OH	0.000	0.121	
11	-	II	-	-	OH	OH	OH	0.000	-0.220	
12	Fructose	-	-	-	-	-	-	0.236	0.007	
13	-	Ι	ОН	ОН	ОН	Cl	OH	0.301	0.529	no
14	-	Ι	OH	Cl	OH	OH	OH	0.699	0.884	
15	-	Ι	OH	OH	OH	Cl	Cl	0.699	1.087	
16	-	Ι	OH	OH	Cl	OH	OH	1.301	0.413	
17	-	Ι	OH	OH	OH	OH	Cl	1.301	1.191	
18	-	II	-	-	Cl	ОН	OH	1.301	0.923	uncertain
19	-	II	-	-	OH	OH	Cl	1.301	1.250	
20	-	Ι	Cl	OH	Cl	OH	Cl	1.398	1.226	
21	-	Ι	OH	OH	Cl	Cl	OH	1.477	1.287	
22	-	Ι	OH	F	F	OH	F	1.602	1.579	
23	-	Ι	ОН	Cl	ОН	ОН	Cl	1.699	2.073	yes
24	-	Ι	OH	OH	Cl	OH	Cl	1.881	1.608	·
25	-	Π	-	-	Cl	OH	Cl	1.903	1.501	
26	-	Π	-	-	Br	OH	Br	1.903	1.910	
27	-	Ι	OH	OH	Cl	Cl	Cl	2.000	2.173	
28	-	Π	-	-	Cl	Cl	Cl	2.000	2.050	yes
29	-	Ι	OH	Cl	Cl	OH	OH	2.079	1.717	·
30	-	Ι	OH	Cl	Cl	Н	Cl	2.176	1.950	
31	-	Ι	OH	Cl	OH	Cl	Cl	2.204	2.796	
32	-	Ι	Cl	Cl	Cl	OH	Cl	2.301	2.338	
33	-	Ι	ОН	Cl	Cl	Cl	ОН	2.342	1.498	uncertain
34	-	Ι	OH	Br	Cl	OH	Cl	2.574	2.836	
35	-	Ι	Н	Cl	Cl	OH	Cl	2.602	2.673	
36	-	Ι	OH	Cl	Cl	OH	Cl	2.813	2.882	
37	-	Ι	OH	Cl	Br	ОН	Br	2.903	2.918	
38	-	Ι	ОН	Cl	Cl	F	Cl	3.000	2.900	yes
39	-	Ι	ОН	Cl	Cl	Cl	Cl	3.477	3.062	v
40	-	Ι	OH	Cl	Cl	Br	Cl	3.477	3.209	
41	-	I	OH	Cl	Cl	Ι	Cl	3.875	3.991	

 Table 1. Log(RS) values of sugars/halosugars

In QSAR study # 1 the descriptor having the highest influence on the Log(RS) value is the "QSAR of molecular orbital energies". This descriptors gives Log(RS) as a linear function of the inverse of the energy differences between the HOMO-1, HOMO, LUMO and LUMO+1 molecular orbitals. When all the molecules from Table 1 had been included in the training set, the same descriptor proved to have the highest influence on the Log(RS) value. This suggests that the Log(RS) value for (halo)sugars correlates with the absorbed radiation wavelengths in the UV-VIS domain.

QSAR study #2

Database: guanidine derivatives, 41 molecules (Fig. 2, Table 2) Dependent property: Log(RS), the values are taken from literature¹⁶ Training set: 33 molecules (Table 2, normal font) Testing set: 8 molecules (Table 2, bold font) Descriptors: "whole molecule" + "grid" Number of significant descriptors: 21

The type (6) QSAR equation for prediction:

 $c_0 = .7139$ $c_1 = -32.6107$ $p_1 - A33 \text{ (electrostatic attraction force, "grid" descriptor)}$ $c_2 = -1749.6464$ $p_2 - F120 \text{ (electrostatic resultant force, "grid" descriptor)}$ $c_3 = -15.4273$ $p_3 - A64 \text{ (electrostatic attraction force, "grid" descriptor)}$

Standard error (training set): 0.356 Fisher F function (training set): 24.4 Kendall cross-validated rank correlation K_{CV} (training set) = .5758 Kendall correlation K (testing set): 0.7857 Standard error (testing set): 0.393

The three testing set molecules having the highest values of Log(RS) have been labeled "recommended for synthesis". The molecule having the smallest Log(RS) value has been labeled "un-recommended for synthesis".

It is remarkable how few significant descriptors there are. Due to how PRECLAV selects the significant descriptors (from a group of almost 1000 computed), a small number of significant descriptors suggest that the training set is not a representative sample for the molecules in Table 2. From the group of 21 retained significant descriptors only 5 are "grid" descriptors. Nevertheless, the equation utilized for prediction contains only "grid" predictors.

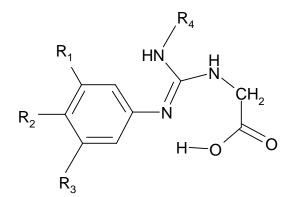


Figure 2. Structure of guanidine derivatives.

Crt. No.	R_1	R_2	R ₃	R_4	LogRS Obs.	LogRS Calc.	Recommended for synthesis
42	Н	CN	Н	CH ₂ CH ₃	2.544	2.891	
43	Cl	Η	Cl	C ₆ H ₃ (3,5-diCl)	3.000	3.140	
44	Н	CN	Н	Н	3.431	2.762	no
45	Н	CN	Н	C ₆ H ₅	3.603	3.739	
46	Н	CN	Н	$C_{6}H_{4}(2-CH_{3})$	3.699	3.886	
47	Н	Н	Н	$(CH(CH_3)C_6H_5 S$	3.699	4.404	
48	CN	Н	Н	$(CH(CH_3)C_6H_5 S$	3.740	4.007	
49	Н	CN	Н	(CH ₂) ₅ CH ₃	3.778	4.038	uncertain
50	NO_2	Н	Η	$(CH(CH_3)C_6H_5 S$	3.778	3.737	
51	Н	CN	Н	$C_{6}H_{4}(4-CH_{3})$	3.845	3.991	
52	Н	NO_2	Н	(CH(CH ₃)C ₆ H ₅ S	3.845	4.448	
53	CF ₃	Н	Н	(CH(CH ₃)C ₆ H ₅ S	3.875	4.085	
54	Н	CN	Н	(CH ₂) ₂ C ₆ H ₅	3.929	4.261	uncertain
55	Н	CN	Н	$(CH(CH_3)C_6H_5 R)$	3.954	4.408	
56	Н	CN	Н	C ₆ H ₄ (3-CH ₃)	3.954	4.158	
57	Н	CN	Н	$C_{6}H_{4}(3-Cl)$	4.000	3.442	
58	Н	CN	Н	Cyc- C ₆ H ₁₁	4.079	3.939	
59	CH ₃	Н	Н	(CH(CH ₃)C ₆ H ₅ S	4.079	4.504	uncertain
60	F	Н	F	(CH(CH ₃)C ₆ H ₅ S	4.176	4.522	
61	Cl	Н	Cl	$cyc-C_7H_{13}$	4.301	4.487	
62	Br	Н	Н	(CH(CH ₃)C ₆ H ₅ S	4.398	4.268	
63	Н	CN	Н	(CH(CH ₃)C ₆ H ₅ S	4.447	4.215	
64	Н	CN	Н	CH ₂ C ₆ H ₅	4.477	4.190	uncertain
65	CH_3	Н	CH ₃	(CH(CH ₃)C ₆ H ₅ S	4.477	4.493	
66	Н	CN	Н	CH_2 -(cyc- C_6H_{11})	4.544	4.689	
67	Cl	Cl	Cl	(CH(CH ₃)C ₆ H ₅ S	4.544	4.346	
68	Cl	Н	Cl	CH_2 -(cyc- C_6H_{11})	4.544	4.805	
69	Н	CN	Н	(CH(CH ₃)-cyc-C ₆ H ₁₁ S	4.699	4.877	yes
70	CH_3	CN	Н	(CH(CH ₃)C ₆ H ₅ S	4.699	4.309	·
71	CH ₃	CN	CH_3	(CH(CH ₃)C ₆ H ₅ S	4.699	4.326	
72	Н	CN	Н	$cyc-C_7H_{13}$	4.778	4.502	
73	Cl	Н	Cl	$cyc-C_8H_{15}$	4.778	4.591	
74	Cl	Н	Cl	(CH(CH ₃)-cyc-C ₆ H ₁₁ S	4.845	4.820	yes
75	Cl	Н	Cl	$CH_2C_6H_5$	4.903	4.358	·
76	Cl	Н	Cl	(CH(CH ₃)C ₆ H ₅ S	5.079	4.401	
77	Н	CN	Н	$cyc-C_{10}H_{19}$	5.176	5.703	
78	Н	CN	Н	$CH(C_6H_5)_2$	5.176	5.138	
79	Cl	Н	Cl	CH(C ₆ H ₅) ₂	5.204	5.122	yes
80	Н	CN	Н	$cyc-C_8H_{15}$	5.230	4.620	v
81	Н	CN	Н	$CH_2C_6H_4(3-CH_3)$	5.301	5.047	
82	Н	CN	Н	cyc-C ₉ H ₁₇	5.301	5.069	

 Table 2. Log(RS) values of guanidine derivatives

In QSAR study # 2 the descriptor having the highest influence on the Log(RS) value is the "grid" descriptor A33. When all the molecules from Table 2 had been included in the training set, the "bond orders sum" descriptor proved to have the highest influence on Log(RS). This suggests that in case of Fig. 2 guanidine derivatives the values of Log(RS) depend on the molecular size and on the un-saturation degree of the chemical bonds. The importance of the size of the molecule is stressed too – using the "moment of inertia C" descriptor – by the QSAR study on guanidines, performed with a very different training set by Katrizky et al.³³

There have been synthesized some guanidines where the R_4 chemical group (see Figure 2) contains a polycyclic system (naphthyl, indanyl, adamantyl, 1,3-benzodioxolil etc.)¹⁶. We have performed numerous other QSAR studies using PRECLAV (that are not included here) with a database including both the molecules from Table 2 and several guanidines with a polycyclic system. No matter how we grouped the molecules in the training and testing sets, the prediction power of the resulting equations was much weaker – for both the training set and the testing set molecules. Therefore, we are drawing the conclusion that the guanidines with a R_4 containing a polycyclic system and the guanidines from Table 2 belong to two different subclasses of guanidinic sweeteners.

QSAR study #3

Database: 3-aminosuccinamic acid derivatives, 41 molecules (Fig. 3, Table 3) Dependent property: Log(RS), values taken from literature¹⁸⁻³¹ Training set: 33 molecule (Table 3, normal font) Testing set: 8 molecule (Table 3, bold font) Descriptors: "whole molecule" + "grid" Number of significant descriptors: 388

The type (6) QSAR equation for prediction:

 $c_0 = -20.8851$

- $c_1 = .8607$
- p₁ QSAR of molecular orbital energies
- $c_2 = -14.8874$
- p₂ A34 (electrostatic attraction force, "grid" descriptor)
- $c_3 = 1.8796$
- p₃ Platt topologic index / Heavy atoms number ratio
- $c_4 = 1.0863$
- $p_4 E(lumo+1) E(homo-1) gap$
- $c_5 = 6.6894$
- p₅ R84 (electrostatic repulsion force, "grid" descriptor)

Standard error (training set): 0.193 Fisher F function (training set): 120.3 Kendall cross-validated rank correlation K_{CV} (training set) = .9129 Kendall correlation K (testing set): 0.5714 Standard error (testing set): 0.715

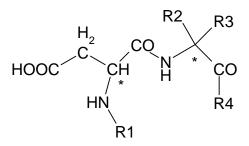


Figure 3. Structure of 3-aminosuccinamic acid derivatives.

Crt. No.	R ₁	R_2	R ₃	R_4	Cfg. in Fig. 3	LogRS Obs.	Log RS Calc.	Reco- mmended fo synthesis
83	Н	Н	CH ₃	O(CH ₂) ₃ CH ₃	L – D	1.041	1.552	5
84	Н	Н	CH_3	OCH ₃	L – D	1.415	1.507	
85	Н	Н	(CH ₂) ₃ CH ₃	OCH ₃	L – D	1.613	2.117	no
86	Н	Н	CH(CH ₃) (CH ₂) ₃ CH ₃	OCH ₃	L – D	1.785	1.771	
87	Н	Н	CH ₃	OC_2H_5	L – D	1.908	1.674	
88	Н	Н	$(CH_2)_2C_6H_5$	OCH ₃	L - L	2.004	2.234	
89	Н	Н	$CH(CH_3)_2$	NHCH(cyc-propyl) ₂	L – D	2.045	2.240	
90	Н	CH ₃	C ₆ H ₅	OCH ₃	L - L	2.179	2.890	uncertain
91	Н	Н	CH ₃	O(CH ₂) ₂ CH ₃	L – D	2.233	1.692	
92	Н	Н	CH ₃	NHCH(CH ₃)(C ₆ H ₅) S	L – D	2.258	2.265	
93	Н	Н	CH_3	O-cyc-hexyl	L – D	2.303	2.315	
94	Н	CH_3	CH ₃	NHCH(C_2H_5)(C_6H_5)	L – D	2.303	2.557	
95	Н	Н	CH ₂ - cyclohexyl	OCH ₃	L – D	2.354	2.833	uncertain
96	Н	Н	cyc-hexyl	NHCH(CH ₂ OCH3) (C ₆ H ₅) \mathcal{R}	L – D	2.400	2.396	
97	Н	Н	CH ₃	$ \begin{array}{c} \text{NHCH}(\text{CH}_2\text{OCH3}) \\ (\text{C}_6\text{H}_5) \mathcal{R} \end{array} $	L – D	2.479	2.474	
98	Н	Н	CH ₃	NH(2,6-diCH ₃ - C ₆ H ₃)	L – D	2.700	2.647	
99	Н	Н	$CH(CH_3)(C_2H_5)$	$\frac{\text{NHCH}(\text{C}_2\text{H}_5)(\text{ C}_6\text{H}_5)}{S}$	L – D	2.700	2.739	
100	Н	Н	CH(CH ₃) ₂	NHCH(CH3)(C ₆ H ₅) <i>S</i>	L – D	2.733	2.820	uncertain
01	Н	Н	COOCH ₃	O- cyc-pentyl	L - L	2.779	2.678	
02	Н	Н	COOC ₂ H ₅	O-(2-CH ₃ - cyc- hexyl)	L–L	2.814	2.788	
			CH ₂ -					
103	Н	Н	(bicyclo[2.2.1]- heptyl)	OCH ₃	L – L	2.904	2.898	
104	$(CH_2)_3C_6H_5$	Н	$CH_2C_6H_5$	OCH ₃	L - L	3.000	3.157	
105	Н	Н	2-furanyl	NHCH(C ₂ H ₅) (C ₆ H ₅) S	L – D	3.080	2.857	uncertain
106	Н	Н	CH(CH ₃) ₂	NHCH(C_2H_5)(C_6H_5)	L – D	3.176	3.126	
107	Н	Н	C_2H_5	NHCH(C ₃ H ₇)(C ₆ H ₅) <i>S</i>	L – D	3.301	2.981	

Table 3. Log(RS) values of 3-aminosuccinamic acid derivatives

108	Н	Н	C_2H_5	NHCH(CH ₂ OCH3) (C ₆ H ₅) \mathcal{R}	L – D	3.398	3.285	
109	(CH ₂) ₂ -t-Bu	Н	CH_3	NHCH(cyc-propyl) ₂	L – D	3.398	3.567	
110	(CH ₂) ₂ -t-Bu	Н	CH(CH ₃) ₂	NHCH(C2H5) (C6H5) S	L – D	3.477	4.471	yes
111	(CH ₂) ₂ C(CH ₃) ₂ C ₆ H ₅	Н	$CH_2C_6H_5$	OCH ₃	L-L	3.602	3.412	
112	(CH ₂) ₂ -t-Bu	Н	C_2H_5	NHCH(CH ₂ OCH3) (C ₆ H ₅) \mathcal{R}	L – D	3.602	3.602	
113	(CH ₂) ₂ -t-Bu	Н	CH(CH ₃) ₂	NHCH(CH ₂ OCH3) (C ₆ H ₅) \mathcal{R}	L – D	3.602	3.487	
114	(CH ₂) ₂ -t-Bu	CH_3	$\mathrm{CH}_2\mathrm{C}_6\mathrm{H}_5$	OCH ₃	L - L	3.740	3.655	
115	Н	Н	COOCH ₃	O-(2-CH ₃ -cyc-hexyl)	L - L	3.845	2.898	uncertain
116	(CH ₂) ₂ -t-Bu	Н	C_2H_5	NHCH(C ₂ H ₅)(C ₆ H ₅) S	L – D	3.903	4.002	
117	(CH ₂) ₃ -2,4-diOH- C ₆ H ₃	Н	$CH_2C_6H_5$	OCH ₃	L-L	4.000	4.124	
118	(CH ₂) ₃ -2,3,4-triOH- C ₆ H ₂	Н	$CH_2C_6H_5$	OCH ₃	L-L	4.000	4.114	
119	Н	Н	CH ₂ -(2- furanyl)	OCH ₃	L – D	4.000	4.045	
120	(CH ₂) ₃ -3,4-diOH- C ₆ H ₃	Н	CH ₂ C ₆ H ₅	OCH ₃	L - L	4.176	3.807	yes
121	(CH ₂) ₃ -3-OH,4- OCH ₃ -C ₆ H ₃	Н	$\mathrm{CH}_{2}\mathrm{C}_{6}\mathrm{H}_{5}$	OCH ₃	L – L	4.398	4.073	
122	(CH ₂) ₃ -3,4,5-triOH- C ₆ H ₂	Н	$CH_2C_6H_5$	OCH ₃	L-L	4.398	4.402	
123	(CH ₂) ₂ -C(CH ₃) ₂ - 3- OH,4-OCH ₃ -C ₆ H ₃	Н	$CH_2C_6H_5$	OCH ₃	L – L	4.699	4.868	

Table 3. Continued

The prediction for the training set molecules is very good (F and K_{CV} have high values).

The prediction for the testing set molecules is poorer (K = 0.5714). Nevertheless, molecule **85**, having the lowest Log(RS) value, is correctly labeled "un-recommended for synthesis", and molecule **120**, having the highest Log(RS) value, is correctly labeled as "recommended for synthesis".

In QSAR study # 3 the descriptor having the highest influence on the value of Log(RS) is the "E(lumo+1) - E(homo-1) gap" descriptor. When all the molecules from Table 3 were included in the training set, the "Platt topologic index / Heavy atoms number ratio" descriptor proved to have the highest influence on Log(RS). This suggests that in the case of dipeptides, the value of Log(RS) depends on the molecular size and on the ramification degree of catena.

QSAR study # 4 Database: 123 molecule (Table 1 + Table 2 + Table 3) *Dependent property*: Log(RS) Training set: 98 molecules (Table 1 + Table 2 + Table 3, without the testing set molecules) *Testing set*: 25 molecules (Table 4) Descriptors: "whole molecule" Number of significant descriptors: 144

The type (6) QSAR equation for prediction: $c_0 = -.3004$ $c_1 = -.4185$ p₁ – Number of O-H single or faint bonds $c_2 = -.1766$ p₂ – Dipole moment (X component) $c_3 = .2548$ $p_3 - 100 * Max.$ atomic nucleophilic reaction index for C atoms $c_4 = 18.0493$ p₄ – Number of triple bonds / Number of bonds ratio $c_5 = .0104$ p₅ – Molecular weight Standard error (training set): 0.485

Fisher F function (training set): 172.5 Kendall cross-validated rank correlation K_{CV} (training set) = 0.7921 Kendall correlation K (testing set): 0.7933 Standard error (testing set): 0.507

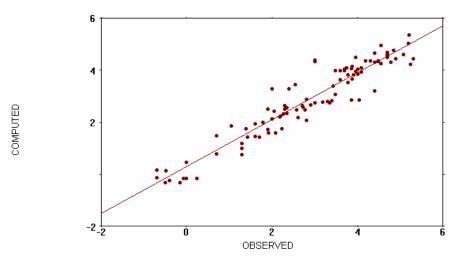


Figure 4. Observed/Computed values of Log(RS) - training set (entire database).

The "recommended for synthesis" group in testing set includes 8 guanidines and 2 dipeptides. The "un-recommended for synthesis" group in testing set includes 6 (halo)sugars and 1 dipeptide.

Molecule	Obs. LogRS	Calc. LogRS	Calc. – Obs.	Recommended for synthesis	
			difference		
82	5.301	4.574	-0.727	yes	
77	5.176	4.871	-0.305	yes	
72	4.778	4.521	-0.257	yes	
68	4.544	4.541	-0.003	yes	
63	4.447	4.442	-0.005	yes	
120	4.176	3.763	-0.413	yes	
118	4.000	3.642	-0.358	uncertain	
54	3.929	4.113	0.184	yes	
52	3.845	4.076	0.231	yes	
48	3.740	4.240	0.500	yes	
111	3.602	4.542	0.940	yes	
109	3.398	3.237	-0.161	uncertain	
105	3.080	3.259	0.179	uncertain	
37	2.903	2.664	-0.239	uncertain	
99	2.700	2.962	0.262	uncertain	
97	2.479	2.833	0.354	uncertain	
93	2.303	2.162	-0.141	no	
28	2.000	2.381	0.381	uncertain	
24	1.881	1.357	-0.524	no	
85	1.613	2.986	1.373	uncertain	
21	1.477	1.905	0.428	no	
17	1.301	0.618	-0.683	no	
13	0.301	0.822	0.521	no	
8	-0.097	-0.236	-0.139	no	
3	-0.523	-0.179	0.344	no	

Table 4. Log(RS) values of testing set molecules (entire database)

In QSAR study # 4 the descriptor having the highest influence on the Log(RS) value is the "Molecular weight" descriptor. When all the molecules from Table 1, Table 2, and Table 3 were included in the training set, the "Percent of oxygen * Maximum charge of oxygen atoms product" descriptor proved to have the highest influence on Log(RS). This suggests that the value of Log(RS) depends on the size of molecules and on the electrostatic interactions involving oxygen atoms.

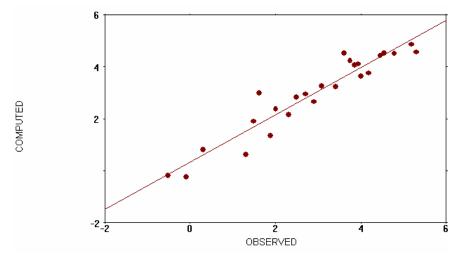


Figure 5. Observed/Computed values of Log(RS) - testing set (entire database).

Conclusions

PRECLAV software classifies the potential sweeteners from the testing set according to the values of Log(RS), in "recommended" or "un-recommended" for synthesis. By comparing the estimated values with the observed Log(RS) values we have found that the classification is mostly correct and thus it has practical value. This is the case even if the training/testing set contains sweeteners from several different classes.

The descriptors having the highest influence on Log(RS) are specific to each class of sweeteners.

The N-phenyl-guanidine-acetic acid derivatives, with a polycyclic system bonded to the nitrogen atom, represent a distinct subclass of N-phenyl-guanidine-acetic acid derivative sweeteners.

Supplementary Material is Available

Global descriptors Grid descriptors

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