Topological Descriptors in Similarity Studies

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1.1. Layer Matrix LM

A layer of vertices located at distance k to the vertex i is defined as: ¹⁻⁴

$$G(i)_k = \left\{ v \middle| v \in V(G); \quad d_{iv} = k \right\}$$
⁽¹⁾

Define the partition of *G* with respect to *i* as:

$$G(i) = \left\{ G(i)_k \; ; \, k \in [0, 1, ..., ecc_i] \right\}$$
(2)

with ecc_i being the *eccentricity* of *i* (*i.e.*, the largest distance from *i* to the other vertices of *G*).

The entries in the layer matrix (of vertex property) LM, is defined as:

$$\left[\mathbf{L}\mathbf{M}\right]_{i,k} = \bigcap_{v \mid d_{i,v} = k} p_v \tag{3}$$

with the most used operation being the summation. The zero column is just the column of vertex properties . Any atomic/vertex property can be considered as pi and any square matrix M can be taken as *info matrix*, *i.e.*, the matrix supplying local/vertex properties as *row sum RS*, *column sum CS* or *diagonal entries* given by the *Walk* matrix^{3,4}.

Layer matrix is a collection of the above defined entries:

$$\mathbf{LM} = \left\{ [\mathbf{LM}]_{i,k}; i \in V(G); k \in [0,1,..,d(G)] \right\}$$
(4)

with d(G) being the diameter of the graph (*i.e.*, the largest distance in *G*). The layer matrix of vertex labeling **LLb** (see below) is the first layer matrix to be constructed. It represents just the graph partitions with respect to all its vertices.

1.2 Shell Matrix SM

Define the entries in the shell/layer matrix (of pair vertex property) SM as: ⁵

$$\left[\mathbf{SM}\right]_{i,k} = \bigcap_{v \mid d_{i,v} = k} \left[\mathbf{M}\right]_{i,v}$$
(5)

with the most used operation being the summation. Shell matrix is a collection of the above defined entries:

$$\mathbf{SM} = \left\{ [\mathbf{SM}]_{i,k}; i \in V(G); k \in [0,1,..,d(G)] \right\}$$
(6)

The zero column, , in case of zero diagonal square info matrix but any other vertex property (written as diagonal entries) can be considered. The above definitions hold in any graph and any square matrix.

• 1.3. Distance Extended Properties

Any property can be multiplied by distance (topological or genuine one) separating vertices in the graph. The way of achieving this "extension" is different, function of matrix and operation used.

• The properties of the above defined matrices are examplified on two graphs:



 The topological descriptors are calculated by the TOPOCLUJ software package 1.0 on the following basic matrices: adjacency, connectivity, distance, 3Ddistance, detour, and four types of Cluj matrices (Figure 1).

TOPOCLUJ	
Calculate basic matrices Adiacency Connectivity Distance Distances Chui Distance Chui Distance Chui Distance Chui Distance Chui Distance Chui Distance Chui Distance Chui Distance Chui Distance Chui Distance Chui Distance Chui Distance Chui Distance Chui Distance Chui Distance Chui Distance Chui Distance Chui Distance Chui Distance Chui Distance Chui Distance Chui Distance Chui Distance Chui Distance Chui Distance Chui Distance <td></td>	
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• 2.1. Layer Matrix LM Building up

Let build up the LLb matrix (Table 1), by using an amended distance matrix, $DLb = ILb + D_e$, where I is the diagonal unity matrix. The partitioning of G_1 with respect to its vertices is obtained by collecting the labeling of vertices located at distance k from the given vertex i (cf (1)). Recall that the non-diagonal entries in the distance matrix D_e count the number of edges on the shortest path joining two vertices i and j, while the diagonal entries are zero.¹

Table 1

				D	Lb(G	<u>_</u>)					LLb(C	<i>G</i> ₁)	
	1	2	3	4	5	6	7	k	0	1	2	3	4
1	1	1	2	3	4	2	3		1	{2 }	{3, 6}	{4, 7}	{5 }
2	1	2	1	2	3	1	2		2	<i>{</i> 1 <i>,</i> 3 <i>,</i> 6 <i>}</i>	{4, 7}	{5}	0
3	2	1	3	1	2	2	1		3	{2, 4, 7}	{1, 5, 6}	0	0
4	3	2	1	4	1	3	2		4	{3, 5}	{2, 7}	{1, 6}	0
5	4	3	2	1	5	4	3		5	{4 }	{3 }	{2, 7}	{1, 6}
6	2	1	2	3	4	6	3		6	{2 }	{1, 3}	{4, 7}	{5}
7	3	2	1	2	3	3	7		7	{3 }	{2, 4}	{1, 5, 6}	0

The most simple and essential is the *counting* property (*i.e.*, the existence of a vertex in a given position is counted by 1, and zero, otherwise). The corresponding layer matrix LC is given in Table 2. Another example is the layer matrix of partial charges LCH, (calculated on G₂).

Table 2

		÷	I	C (<i>G</i> ₁)					L	$CH(G_2)$		
i¥k	0	1	2	3	4	RS	0	1	2	3	4	RS
1	1	1	2	2	1	7	0.087	0.186	0.282	-0.333	-0.223	0
2	1	3	2	1	0	7	0.186	0.370	-0.333	-0.223	0	0
3	1	3	3	0	0	7	0.195	-0.147	-0.048	0	0	0
4	1	2	2	2	0	7	0.015	-0.028	-0.162	0.175	0	0
5	1	1	1	2	2	7	-0.223	0.015	0.195	-0.162	0.175	0
6	1	1	2	2	1	7	0.087	0.186	0.282	-0.333	-0.223	0
7	1	1	2	3	0	7	-0.348	0.195	0.201	-0.048	0	0
CS	7	12	14	12	4		0	0.776	0.418	-0.924	-0.271	0
CS·k		12	28	36	16	92 ^a		0.776	0.835	-2.771	-1.082	-2.241
$CS \cdot 1/k$		12	7	4	1	24 ^b		0.776	0.209	-0.308	-0.068	0.610

2004/3/30 (a) 2x Wiener index W_{2} (b) 2x Harary index H

- Note that the rows in LC represent just the vertex distance degree sequences DDS_i (i.e., the number of vertices located at distance k from i)¹ while the column sums CS represent the graph DDS_k.
- LC is calculated when layer matrix is performed by TOPOCLUJ with no property is selected (see Figure 2).
- **LCH** is calculated by clicking on the "atomic charge" in the "Properties" second window.

File Calculate Operal	alculate layer matrix Matrix list	X	-DX	
	G1_AD G1_CON G1_CON G1_INV_DI G1_D3D G1_D2 G1_DE G1_CIDi G1_CIDi G1_CFDi G1_CFDe G1_CFDe G1_TRANS_CIDe			
	Properties atomic charge Col sum Diagonal entries Group mass Row sum SGI			
	<i>Options</i> Keep matrix Xindex Cindex Polynomial			
	🗸 OK 🛛 🗶 Cancel			

Figure 2. Window of layer matrix calculation; properties for weighting schemes and topological indices/polynomial as options 2004/3/30 Within TOPOCLUJ program the partial charges are calculated as follows:

$$ch_{i,j} = \log \left[(S_j / S_i)^{1/(d_{i,j})^2} \right]$$
(8)
$$ch_i = \sum_j ch_{i,j}$$
(9)

- In the above relations, S_i , S_j represent the Sanderson group electronegativities SGE_s , calculated for the hydride groups (*i.e.*, the heavy atoms with their surrounding hydrogen atoms) in the molecule.
- The log function provides the sign for the partial charge ch_{ij} , viewed as a distance decreasing perturbation (see also ref. 13) of the *i*th SGE produced by the atom *j* (see the exponent, where d_{ij} is the Euclidean distance separating atoms *i* and *j*).
- The $N \times N$ array collecting the entries ch_{ij} is the charge matrix CH, whose row sums ch_i represent the total partial charge on hydride group/atom *i* in the molecule (column k = 0 in LCH Table 2).
- Distance-extended property sum indicates, in this example, the location of the negative partial charge on the more eccentric atoms (*e.g.*, N and O).



By multiplying *CS* by k (or 1/k) distance-extended properties are obtained. In the above example, Wiener⁶⁻⁸ *W* and Harary⁹⁻¹¹ *H* indices are thus obtained (twice value, in Table 2).

Reciprocal matrices are calculable by the window "Mathematical operations", and next "Reciprocal".

Topological indices I are calculated as the *half sum of the entries* in a square matrix (*i.e.*, the matrix supplying the property p) :

$$I = \sum_{i < j} [\mathbf{M}]_{i,j} = (1/2) \cdot \mathbf{u} \cdot \mathbf{M} \cdot \mathbf{u}^{\mathrm{T}}$$
(7)

with **u** and **uT** being the unity vector (of dimension N, *i.e.*, the number of vertices in G) and its transpose, respectively.¹²

2.2. LM of Symmetric Square Matrices

- Layer matrix of walk degrees L^eW. The walk degree (of length e) equals the row sum in the adjacency matrix A (raised at power e). For e = 1 one recovers the classical vertex degree (*i.e.*, vertex valency).^{3,4}
- Entries in A matrix equal unity when two vertices *i* and *j* are connected by an edge and zero otherwise.
- The distance extended property is now the valency¹⁴ and the valency-distance index was patterned by several authors^{12,15-18} (see footnote, Table 3). In matrix terms, the Cramer product AD_e is calculated.

Table 3

		L	¹ W (0	G ₁)				J	L ² W ((<i>G</i> ₁)				L	⊿³ ₩ (G	÷_)		
i¥k	0	1	2	3	4	RS	0	1	2	3	4	RS	0	1	2	3	4	RS
1	1	3	4	3	1	12	3	5	9	7	2	26	5	12	17	14	4	52
2	3	5	3	1	0	12	5	12	7	2	0	26	12	22	14	4	0	52
3	3	6	3	0	0	12	6	12	8	0	0	26	12	26	14	0	0	52
4	2	4	4	2	0	12	4	8	8	6	0	26	8	16	18	10	0	52
5	1	2	3	4	2	12	2	4	6	8	6	26	4	8	12	18	10	52
6	1	3	4	3	1	12	3	5	9	7	2	26	5	12	17	14	4	52
7	1	3	5	3	0	12	3	6	9	8	0	26	6	12	20	14	0	52
CS	12	26	26	16	4		26	52	56	38	10		5	108	112	74	18	
CS·k		26	52	48	16	142 ^a		52	112	114	40	318		108	224	222	72	626
CS·1/k		26	13	5.3	1	45.3		52	28	12.7	2.5	95.2		108	56	24.7	4.5	193.2

(a) 2x**I** (**I** = Degree-Distance Index; Ivanciuc, Dobrynin, Schultz, Estrada - see text)

- The walk matrix W (Figure 3), running the ^eWM algorithm (Diudea, Topan and Graovac⁴), allows to elude the raising of a square matrix at a power *e*.
- It evaluates a (topological) property of a vertex *i*, by iterative summation of the first neighbors contributions.
- The algorithm is extended to account for general graphs (with loops and multiple bonds):

^eWM algorithm

M is any square matrix, I is the unity diagonal matrix and *Li* is the number of loops attached to the atom *i*.

$$\mathbf{M} + \mathbf{I} = {}^{e} \mathbf{W}_{M}; \ e = 0 \tag{10}$$

$$[{}^{e+1}\mathbf{W}_{M}]_{ii} = 2L_{i}[{}^{e}\mathbf{W}_{M}]_{ii} + \sum_{j \neq i} ([\mathbf{M}]_{ij}[{}^{e}\mathbf{W}_{M}]_{jj})$$
(11)

$$[{}^{e} \mathbf{W}_{M}]_{jj} = 2L_{j}[{}^{e-1} \mathbf{W}_{M}]_{jj} + \sum_{k \neq j} ([\mathbf{M}]_{jk}[{}^{e-1} \mathbf{W}_{M}]_{kk})$$
(12)

$$[^{e+1}\mathbf{W}_M]_{ij} = [^e\mathbf{W}_M]_{ij} = [\mathbf{M}]_{ij}$$
(13)



E	TOPOCLUJ	W matrix calculation	×	
	File Calculate Operal	Matrix list		
		G1 AD G1_CON G1_DI G1_D3D G1_DE G1_CJDi G1_CJDe G1_CFDi G1_CFDe G1_CFDe G1_CFDe G1_CFDe		
		- Properties atomic charge Group mass SGI	-	
		, □ <u>Keep matrix</u> <u>1</u> <u>Power</u>		
		V OK X Cancel		

Figure 3. Window of W matrix calculation (weighted by a chosen property

^eWM algorithm

The algorithm starts with the diagonal entries $[{}^{e}\mathbb{W}M]_{ii} = 1$. In each of the following steps $[{}^{e}\mathbb{W}M]_{ii}$ become the row sums RS_{i} of the matrix **M** raised at a power e, **M**^e:

$$[{}^{e}\mathbf{W}_{M}]_{ii} = \sum_{j} [\mathbf{M}^{e}]_{ij} = {}^{e}w_{M,i}$$
(14)

They represent *walk degrees*, ${}^{ew}M_i$, weighted by the property collected in **M**. The sum of all diagonal entries in ${}^{e}W_M$ is twice the global graph invariant ${}^{e}WM$, called *molecular walk count*:

$$\sum_{i}^{e} w_{M,i} = 2^{e} W_{M} = 2^{e} W_{M}(G)$$
(15)

In the above, $\mathbf{M} = \mathbf{A}$ or **CON**. When $\mathbf{M} = \mathbf{D}$, then ^{*e*}*WM* defines the Wiener number of rank e.²⁷

- To account for the general graphs, the algorithm needs the specification of the atoms bearing loops (Figure 4)
- It is input as a binary numbers column under the name "aproperty aloop" in the file of properties "name.prp" provided by the TOPOCLUJ program.
- In this case, the proper matrix is the connectivity matrix CON, whose non-diagonal entries are just the conventional bond orders: 0, 1, 2, 3 and 1.5, for non-bonding, single, double, triple and aromatic bonds.
- If the graph has no loops, the classical ^eWM algorithm is recovered

TOPOCLUJ	Calculate layer matrix	×	
File Calculate Operat	Matrix list G1_AD G1_CON G1_INV_DI G1_D30 G1_D5 G1_D5 G1_CD5 G1_CD6 G1_CFD6		
	Properties atomic charge Col sum Bigonal entries Broup mass Row sum SGI		
	Options Keep matrix Xindex Cindex Polynomial		
	V OK X Can	cel	

Figure 4. Window of local properties ("aproperty", in a "name.prp" output file)

Examples of ${}^{e}W_{M}$ are given in Tables 4 for G_{2i} once for no loops and next for loops at atoms 5 and 7 (representing heteroatoms with unshared electrons in the loops). The parameter *e* is 1 and 2, respectively.

Tab	le 4 .1	l. Wa	alk Co	ount i	in the	gener	ral Gi	caph G ₂						
		\mathbf{L}^{1}	W (C	ON(C	$(\bar{r}_2))$					L^1W	(CON	loop	$p(G_2))$	
1	1	1	0	0	0	0	0	1	1	0	0	0	0	0
2	1	3	1	0	0	1	0	1	3	1	0	0	1	0
3	0	1	4	1	0	0	2	0	1	4	1	0	0	2
4	0	0	1	4	3	0	0	0	0	1	4	3	0	0
5	0	0	0	3	3	0	0	0	0	0	3	5	0	0
6	0	1	0	0	0	1	0	0	1	0	0	0	1	0
7	0	0	2	0	0	0	2	0	0	2	0	0	0	4
		Sum c	of diag	onal el	lement	s = 18			Sum	of diag	onal el	lement	s = 22	

Table 4.2

		L^{2}	W (C	CON($(G_2))$					L ²	N		
					2				(CC	N_lo	op(G ₂))	
1	3	1	0	0	0	0	0	3	1	0	0 0	0	0
2	1	6	1	0	0	1	0	1	6	1	0 0	1	0
3	0	1	11	1	0	0	2	0	1	15	1 0	0	2
4	0	0	1	13	3	0	0	0	0	1	1 3 9	0	0
5	0	0	0	3	12	0	0	0	0	0	3 22	0	0
6	0	1	0	0	0	3	0	0	1	0	0 0	3	0
7	0	0	2	0	0	0	8	0	0	2	0 0	0	16
			0	6.11			= (0	e 1.			0.4	

Sum of diagonal elements = 84

Sum of diagonal elements = 56

Distance (edge) matrix D_e

The property in column k = 0 is the row sum in the distance matrix $RS(D_e)$ and the corresponding LM is called *layer of distance sum* LD_eS .

Table 5 $\mathbf{D}_{\rho}(G_{1})$ $LD_{\rho}S(G_{1})$ $i \neq k$ RS RS 92^a CS ª CS 92ª CS·k 1260^b $CS \cdot 1/k$ 56.67 302.67 (a) 2xW; (b) $u(D_{a}D_{a})uT$

- The distance extended property is just the (topological) distance. In matrix terms, it means the Cramer product D_eD_e (see footnote b, Table 5 and Figure 5).
- Similar calculations cam be performed on the detour matrix Δ_e (with the non-diagonal entries counting the number of edges on the longest path joining two vertices *i* and *j*, while the diagonal entries are zero).^{9,28}

Distance and Detour (path) matrices D_p and Δ_p

The path-defined distance and detour matrices are calculable by the "Combinatorial matrix" command (Figure 5):⁹

$$[\mathbf{D}_{p}]_{ij} = \begin{cases} N_{p,(i,j)}; (i,j) \in D(G), & \text{if } i \neq j \\ 0 & \text{if } i = j \end{cases}$$
(16)

$$[\boldsymbol{\Delta}_{p}]_{ij} = \begin{cases} N_{p,(i,j)}; (i,j) \in \Delta(G), & \text{if } i \neq j \\ 0 & \text{if } i = j \end{cases}$$
(17)

$$N_{p,(i,j)} = {\begin{bmatrix} \mathbf{M}_{e}]_{ij} + 1 \\ 2 \end{bmatrix}} = (1/2) \left[([\mathbf{M}_{e}]_{ij})^{2} + [\mathbf{M}_{e}]_{ij} \right], \quad \mathbf{M} = \mathbf{D}; \Delta$$
(18)

where $N_{p,(i,j)}$ is the number of all internal paths²⁹ of length $1 \le |p| \le |(i,j)|$ included in the path (i,j).

File Calculate	Operation Window Help			
	IIII Matrix list			
	W matrix Walk operator Layer matrix Shell matrix	Matrix sum Matrix difference Reciprocal Cramer product Hadamard product		
		Eigen values and vectors Combinatorial matrix		
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2.3. LM of Unsymmetric Square Matrices
An unsymmetric matrix, say the product matrix AD_e, can participate either by its *RS* or *CS*, thus providing two different LMs (Table 6 and below).
Extension by distance is equivalent to the Cramer multiplication to the left by D_e (of the matrix product AD_e - see footnote a, Table 6).
PROPERTIES OF LAYER MATRICES

Table 6

	LA	D_RS	$\delta(G_1)$						A	D((7 1)				
i¥k	0	1	2	3	4	RS		1	2	3	4	5	6	7	RS
1	10	39	46	35	12	142		1	0	1	2	3	1	2	10
2	39	56	35	12	0	142		4	3	4	7	10	4	7	39
3	36	74	32	0	0	142		7	4	3	4	7	7	4	36
4	26	48	48	20	0	142		6	4	2	2	2	6	4	26
5	12	26	36	48	20	142		3	2	1	0	1	3	2	12
6	10	39	46	35	12	142		1	0	1	2	3	1	2	10
7	9	36	65	32	0	142		2	1	0	1	2	2	1	9
CS	142	318	308	182	44		CS	24	14	12	18	28	24	22	142
CS·k		318	616	546	176	1656 ^a									
CS·1/k		318	154	60.67	11	543.67									

(a) $\mathbf{u}(\mathbf{D}_e(\mathbf{A}\mathbf{D}_e)\mathbf{u}^{\mathrm{T}}$

2.3. LM of Unsymmetric Square Matrices. Walk operator^{14,19,22} W_(M1,M2,M3)

It is defined as (see Figure 6):¹⁹

$$[\mathbf{W}_{(\mathbf{M}_1,\mathbf{M}_2,\mathbf{M}_3)}]_{ij} = {}^{[\mathbf{M}_2]_{ij}} W_{\mathbf{M}_1,i}[\mathbf{M}_3]_{ij} = [RS((\mathbf{M}_1)^{[\mathbf{M}_2]_{ij}})]_i[\mathbf{M}_3]_{ij}$$
(19)

where $W_{\mathbf{M}1,i}$ is the walk degree of elongation $[\mathbf{M}_2]_{ij}$, of the vertex *i*, weighted by the property collected in matrix \mathbf{M}_1 (*i.e.*, the *i*th row sum of the matrix \mathbf{M}_1 , raised to power $[\mathbf{M}_2]_{ij}$). The diagonal entries are zero.

This matrix, that mixes three square matrices, is a true matrix operator (see below).

File Calculate Operation Window Help	
Source matrix by Walk operator X Source matrix Selected matrix g1_AD g1_AD g1_D1 g1_D1 g1_D3D > g1_CDN g1_DE g1_CDN g1_DE g1_CDN > g1_D3D > g1_CDe >> g1_CPDi < g1_CPDe < g1_CPDe < g1_CPDe < g1_CH <	
Keep matrix ✓ 0K ✓ 0K ✓ Cancel	
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Figure 6. Window of the Walk operator

2. PROPERTIES OF LAYER MATRICES

- Within the W_(M1,M2,M3) matrix operator, the Hadamard algebra works.
- The CS recovers the RS/CS of the corresponding Cramer matrix product M1M3
- The RS equals the pairwise Hadamard product of the two properties collected in M₁ and M₂. The last result has no correspondence in the Cramer algebra.
- Examples are given for $M_1 = A$ and $M_3 = D_2$ in Tables 7 and 8 (see also footnote a, Table 3).

W_(M1,M2,M3) matrix operator and the Hadamard algebra

In case of matrix $W_{(M1,1,M3)}$, (with $M_2 = 1$, *i.e.*, the matrix having all non-diagonal entries unity) the meaning of their vector sums is given²² in eqs. (20) to (22).

$$CS(\mathbf{W}_{(\mathbf{M}1,\mathbf{1},\mathbf{M}3)}) = CS(\mathbf{M}_{1}\mathbf{M}_{3})$$

$$CS(\mathbf{W}_{(\mathbf{M}3,\mathbf{1},\mathbf{M}1)}) = RS(\mathbf{M}_{1}\mathbf{M}_{3})$$
(20)
(21)

 $RS(\mathbf{W}_{(\mathbf{M}1,\mathbf{1},\mathbf{M}3)}) = RS(\mathbf{W}_{(\mathbf{M}3,\mathbf{1},\mathbf{M}1)}) = RS(\mathbf{M}_1) \bullet RS(\mathbf{M}_3)$ ⁽²²⁾

Layer Matrices of Unsymmetric W(M1,M2,M3)

Table 7

	LW	(A,1,E	RS	$G(G_1)$				1	W _{(A,1}	,De)(C	ř ₁)				
i¥k	0	1	2	3	4	RS		1	2	3	4	5	6	7	R S ^c
1	15	30	42	38	17	142		0	1	2	3	4	2	3	15
2	30	57	38	17	0	142		3	0	3	6	9	3	6	30
3	27	68	47	0	0	142		6	3	0	3	6	6	3	27
4	24	44	44	30	0	142		6	4	2	0	2	6	4	24
5	17	24	27	44	30	142		4	3	2	1	0	4	3	17
6	15	30	42	38	17	142		2	1	2	3	4	0	3	15
7	14	27	54	47	0	142		3	2	1	2	3	3	0	14
CS	142	280	294	214	64		<i>CS</i> ^b	24	14	12	18	28	24	22	142
CS·k		280	588	642	256	1766 ^a									
$CS \cdot 1/k$		280	147	71.33	16	514.33									

(a) $\mathbf{u}(\mathbf{D}_{e}(\mathbf{W}_{(\mathbf{A},\mathbf{1},\mathbf{D}e)}))\mathbf{u}T$; (b) $CS(\mathbf{W}_{(\mathbf{A},\mathbf{1},\mathbf{D}e)}) = CS(\mathbf{A}\mathbf{D}_{e})$; (c) $RS(\mathbf{W}_{(\mathbf{A},\mathbf{1},\mathbf{D}e)}) = RS(\mathbf{A}) \bullet RS(\mathbf{D}_{e})$

Layer Matrices of Unsymmetric W_(M1,M2,M3)

Table 8

	LW	, (A,1,Da	_{e)} _CS	$G(G_1)$						V	V _{(De,}	1,A) (G	; ₁)		
i¥k	0	1	2	3	4	RS		1	2	3	4	5	6	7	RS
1	24	14	36	40	28	142		0	15	0	0	0	0	0	15
2	14	60	40	28	0	142		1 0	0	10	0	0	10	0	30
3	12	54	76	0	0	142		0	9	0	9	0	0	9	27
4	18	40	36	48	0	142		0	0	12	0	12	0	0	24
5	28	18	12	36	48	142		0	0	0	17	0	0	0	17
6	24	14	36	40	28	142		0	15	0	0	0	0	0	15
7	22	12	32	76	0	142		0	0	14	0	0	0	0	14
CSc	142	212	268	268	104		CS ^b	1 0	39	36	26	12	10	9	142
CS·k		212	536	804	416	1968 ^a									
$CS \cdot 1/k$		212	134	89.33	26	461.33									

(a) $\mathbf{u}(\mathbf{D}^{e}(\mathbf{D}_{e}\mathbf{A})\mathbf{u}\mathbf{T};$ (b) $CS(\mathbf{W}(\mathbf{D}_{e},\mathbf{1},\mathbf{A})) = RS(\mathbf{A}\mathbf{D}_{e});$ (c) $CS(\mathbf{L}\mathbf{W}(\mathbf{A},\mathbf{1},\mathbf{D}_{e})) = CS(\mathbf{L}(\mathbf{A}\mathbf{D}_{e}))$

3. SHELL MATRICES

• 3.1. SM of Basic Square Matrices

Let us consider the behavior of the basic symmetric adjacency
 A and distance D_e matrices. Since the first matrix is based on the connectivity relation, the corresponding SM will have only one column,

at k = 1 (along with the non-related k = 0 column).

SM are calculable by TOPOCLUJ, see Figure 7.

As a general property of SMs, *RS* vector equals *RS* in the info matrix M.

File Calculate Operation Window Help	_OX	-
Calculate shell matrix Matrix list g1_AD g1_CON g1_D3D g1_DE g1_CiDi g1_CPe g1_CFDe g1_CFDe g1_CH Variation Variation		
	10:21:16 AM //	

3.1. SM of Basic Square Matrices

Table 9

		S	A(<i>G</i>))	2	$\sum_{k=1}^{d(G)}$		S	$\mathbf{D}_{e}(\mathbf{C})$	5 ₁)	$\sum_{k=1}^{d(G)}$	
	0	1	2	3	4		0	1	2	3	4	
$i \notin k$												
1	1	1	0	0	0	1	1	1	4	6	4	15
2	1	3	0	0	0	3	1	3	4	3	0	10
3	1	3	0	0	0	3	1	3	6	0	0	9
4	1	2	0	0	0	2	1	2	4	6	0	12
5	1	1	0	0	0	1	1	1	2	6	8	17
6	1	1	0	0	0	1	1	1	4	6	4	15
7	1	1	0	0	0	1	1	1	4	9	0	14
CS	7	12				12 ^a	7	12	28	36	16	92 ^b
CS·k		12				12		12	56	108	64	240 ^c
$CS \cdot 1/k$		12				12		12	14	12	4	42

(a) 2x e; (b) 2xW; (c) $u(D_e \bullet D_e)u^T$

3.1. SM of Basic Square Matrices

- In case of SD_e , the distance extended property is again the distance but now the extension is equivalent to the Hadamard product $D_e \cdot D_e$.
- Recall that this kind of matrix product:²³ $[\mathbf{M}_a \cdot \mathbf{M}_b]_{ij} = [\mathbf{M}_a]_{ij} [\mathbf{M}_b]_{ij}$, operating within SM matrices, is basically different from the Cramer algebra working in case of LM matrices (see above).
- The Wiener matrices W_e and W_p are defined only on trees.^{24,25} They are calculable as the symmetric Cluj matrices (see the next section).

3. SHELL MATRICES

• 3.2. SM of Cluj Matrices

- The unsymmetric Cluj matrix UCJ is defined on the distance concept^{26,27} (for other extensions see refs. ²⁸⁻³¹). In trees, its non-diagonal entries count the paths going to *j* through *i*, the number of which equals that of vertices located closer to *i* than to *j*. It is just the cardinality of the set of vertices/atoms obeying such condition;
 Since in cycle-containing graphs more than one path could
 - Since in cycle-containing graphs more than one path could join *i* and *j* (and thus providing different sets $V_{i,p(i,j)_k}$ of vertices, referred to *i*, with respect to the path $p(i,j)_k$ the entries will be the maximal cardinality value, over all the paths $p(i,j)_k$:

$$V_{i,p(i,j)_{k}} = \left\{ v \mid v \in V(G); d_{iv} < d_{jv}; p(i,v)_{h} I p(i,j)_{k} = \{i\}; \}; h, k = 1,2,... \right\}$$

$$[UCJ]_{ij} = \max_{k=1,2,...} |V_{i,p(i,j)_{k}}|$$
(23)
(24)

The diagonal entries are zero. The Cluj matrices are defined in any connected graph and is worthy to note that they were designed as an extension of the Wiener matrices (see below).

Any other property (*e.g.*, a property specifying the chemical nature of vertices) and any mathematical operation (other than summation) can be considered in view of defining the entries in the Cluj matrices of property.^{9,39} We limit here to the counting property, so that the entries will be integers.

The graph-theoretical Cluj matrices are calculable as "basic matrices" by **TOPOCLUJ**.

]	Fable 1	0														
			S	UCJ(G_l)		$\sum_{k=1}^{d(G)}$			U	CJ(C	(\vec{r}_l)				
	i¥ k	0	1	2	3	4		_	1	2	3	4	5	6	7	RS
	1	1	1	2	2	1	6	-	0	1	1	1	1	1	1	6
	2	1	15	6	3	0	24		6	0	3	3	3	6	3	24
VIEW	3	1	15	13	0	0	28		4	4	0	5	5	4	6	28
A D. D.	4	1	8	4	4	0	16		2	2	2	0	6	2	2	16
	5	1	1	1	2	2	6		1	1	1	1	0	1	1	6
	6	1	1	2	2	1	6		1	1	1	1	1	0	1	6
	7	1	1	2	3	0	6		1	1	1	1	1	1	0	6
	CS	7	42	30	16	4	92 ^a	CS	15	10	9	12	17	15	14	92
	CS·k		42	60	48	16	166 ^b									
	$CS \cdot 1/k$		42	15	5.33	1	63.33									

(a) 2x Wiener index *W*; (b) 2x hyper-Wiener index *WW*

- The column sums in the shell matrix SUCJ represent just the distancebased decomposition of the Cluj property.
- The distance-extended property represents Cluj fragments and the involved equivalent matrix operation is $UCJ \circ D_e$. Note that the Hadamard product is symmetric (*i.e.*, the same matrix product is obtained by operating both to the left and to right side).
- The extension by the reciprocal distance is important in modeling intra or intermolecular phenomena, which show decreasing values as distance between the involving partners increases.
- In trees, the distance extended Cluj fragments equal to the hyper-Wiener index contributions (see footnote b).
- Also note that the product
 - $UCJ \circ 3DD_e$

leads to a property extended by the Euclidean distance.

The row sum *RS* and column sum *CS* in **UCJ** are related to those in the basic matrices as:

$$RS(\mathbf{UCJ}) = RS(\mathbf{W}_e) \tag{25}$$

$$CS(\mathbf{UCJ}) = CS(\mathbf{D}_e)$$
⁽²⁶⁾

The *RS* and *CS* in distance extended matrix **D_UCJ** are related to the above basic matrices, defined for all vertex pairs:

$$RS(\mathbf{D}_{\mathbf{U}}\mathbf{U}\mathbf{C}\mathbf{J}) = RS(\mathbf{W}_{p})$$
⁽²⁷⁾

$$CS(\mathbf{D}_{\mathbf{U}}\mathbf{U}\mathbf{C}\mathbf{J}) = CS(\mathbf{D}_{p})$$
⁽²⁸⁾

In (25) and (27) W_e and W_p represent the Wiener matrices defined on edge and path, respectively.

Matrices **D_UCJ** and **D**_p are illustrated in Table 11.

	Tabl	e 11																
		_	D_I	UCJ	(G_l)							D	$O_p(G$	² ₁)				
	i	1	2	3	4	5	6	7	RS		1	2	3	4	5	6	7	RS
	1	0	1	2	3	4	2	3	15		0	1	3	6	10	3	6	29
	2	6	0	3	6	9	6	6	36		1	0	1	3	6	1	3	15
	3	8	4	0	5	10	8	6	41		3	1	0	1	3	3	1	12
NUMBER OF	4	6	4	2	0	6	6	4	28		6	3	1	0	1	6	3	20
	5	4	3	2	1	0	4	3	17		10	6	3	1	0	10	6	36
	6	2	1	2	3	4	0	3	15		3	1	3	6	10	0	6	29
	7	3	2	1	2	3	3	0	14		6	3	1	3	6	6	0	25
-																		
	CS	29	15	12	20	36	29	25	166 ^a	CS	29	15	12	20	36	29	25	166 ^a

(a) 2x hyper-Wiener index *WW*

 Despite the different distribution of numbers (due to the reversed meaning: each entry count the paths going to *i* through *j*), the *CS* in the shell matrix SUCJ^T of Cluj matrix transpose (Table 12) are identical to those in SUCJ matrix (which is an expected result).

Table 12

		S (UCJ	^T ,(G	\tilde{r}_1)	$\sum_{k=1}^{d(G)}$			(UCJ)	$^{\mathrm{T}}(G_{j})$)			
i	0	1	2	3	4			1	2	3	4	5	6	7	RS
¥1 <i>k</i>	1	6	5	3	1	15		0	6	4	2	1	1	1	15
2	1	6	3	1	0	10		1	0	4	2	1	1	1	10
3	1	6	3	0	0	9		1	3	0	2	1	1	1	9
4	1	6	4	2	0	12		1	3	5	0	1	1	1	12
5	1	6	5	4	2	17		1	3	5	6	0	1	1	17
6	1	6	5	3	1	15		1	6	4	2	1	0	1	15
7	1	6	5	3	0	14		1	3	6	2	1	1	0	14
CS	7	42	30	16	4	92ª	CS	6	24	28	16	6	6	6	92ª
CS·k		42	60	48	16	166 ^b									
<i>CS</i> •1/ <i>k</i>		42	15	5.33	1	63.33									

(a) 2xW; (b) 2xWW

Simmetric Cluj Matrices

The symmetric matrix can be obtained from **UCJ** matrix by the Hadamard product with its transpose:

 $\mathbf{CJ} = \mathbf{UCJ} \bullet \mathbf{UCJ}^{\mathrm{T}}$

(29)

In trees, the following relations hold:

- $\mathbf{CJ} = \mathbf{CJ}_p = \mathbf{W}_p \tag{30}$
- $\mathbf{CJ}_{e} = \mathbf{W}_{e} = \mathbf{CJ}_{p} \bullet \mathbf{A}$ ⁽³¹⁾

Simmetric Cluj Matrices

- The CS in the shell matrix SCJ represent contributions to the hyper-Wiener global index (see -Table 13 - footnote a).
- The corresponding extension by distance is equivalent to $CJ_p \circ D_e$ (and also $W_p \circ D_e$).
- In cycle-containing graphs, no relation exists between the Cluj matrices and Wiener matrices (the last ones being not defined in such graphs).

SM of Symmetric Cluj Matrices

Table 13

		S	SCJ(C	\vec{r}_{l})					C	$C\mathbf{J}(G$	₁)				
i¥ k	0	1	2	3	4	$\sum_{k=1}^{d(G)}$	_	1	2	3	4	5	6	7	RS
1	1	6	5	3	1	15	-	0	6	4	2	1	1	1	15
2	1	24	9	3	0	36		6	0	12	6	3	6	3	36
3	1	28	13	0	0	41		4	12	0	10	5	4	6	41
4	1	16	8	4	0	28		2	6	10	0	6	2	2	28
5	1	6	5	4	2	17		1	3	5	6	0	1	1	17
6	1	6	5	3	1	15		1	6	4	2	1	0	1	15
7	1	6	5	3	0	14		1	3	6	2	1	1	0	14
CS	7	92	50	20	4	166 ^a	CS	15	36	41	28	17	15	14	166
CS·k		92	100	60	16	268 ^b									
<i>CS</i> ·1/ <i>k</i>		92	25	6.67	1	124.67									

(a) 2x hyper Wiener index WW; (b) 2x Tratch index Tr

Shell matrix of the walk operator $W_{(A,1,De)}$

Table 14

		,	SW _{(A,1}	(G)	<i>l</i>)				V	V _{(A,1,}]	De)(G	₁)			
i¥k	0	1	2	3	4	$\sum_{k=1}^{d(G)}$		1	2	3	4	5	6	7	RS
1	1	1	4	6	4	15	-	0	1	2	3	4	2	3	15
2	1	9	12	9	0	30		3	0	3	6	9	3	6	30
3	1	9	18	0	0	27		6	3	0	3	6	6	3	27
4	1	4	8	12	0	24		6	4	2	0	2	6	4	24
5	1	1	2	6	8	17		4	3	2	1	0	4	3	17
6	1	1	4	6	4	15		2	1	2	3	4	0	3	15
7	1	1	4	9	0	14		3	2	1	2	3	3	0	14
CS	7	26	52	48	16	142 ^a	CS	24	14	12	18	28	24	22	142
CS·k		26	104	144	64	338 ^b									
<i>CS</i> ·1/ <i>k</i>		26	26	16	4	72°									

(a) $u(AD_e)u^T$; (b) $u(A(D_e \bullet D_e))u^T$; (c) $u(A(D_e \bullet RD_e))u^T$

4. INDICES CALCULATED ON LAYER AND SHELL MATRICES

4.1. Indices of centrality, *C(M)*; M = LM/SM:

$$C(M)_{i} = \left[\sum_{k=1}^{ecc} \left(\left[\mathbf{M} \right]_{ik}^{2k} \right)^{1/(ecc)^{2}} \right]^{-1}$$
(32)

$$C(M) = w \sum_{i} C(M)_{i}$$
⁽³³⁾

where *ecc* is the maximal distance in $G(i.e., \max d(i,k))$ and w is a weighting factor

INDICES CALCULATED ON LAYER AND SHELL MATRICES

4.1. Indices of centrocomplexity, X(M); M = LM/SM:

$$X(M)_{i} = \left[\sum_{j=0}^{ecc} M_{ij} * 10^{-z_{i}}\right]^{-1} * t_{i}$$
(34)

$$X(M) = w \sum_{i} X(M)_{i}$$
(35)

An example given in Table 15, for the layer matrix **LCON** (with p_i being the row sum *RS* in the connectivity matrix **CON** and w = 1).

INDICES CALCULATED ON LAYER MATRICES

Table 15

LCON_ $RS(G_2)$; w = 1

i¥k	0	1	2	3	4	C_i	X _i
1	1	3	5	6	3	0.1579	1.3563
2	3	6	6	3	0	0.2312	3.6630
3	4	9	5	0	0	0.3557	4.9500
4	4	7	5	2	0	0.2458	4.7520
5	3	4	4	5	2	0.1711	3.4452
6	1	3	5	6	3	0.1579	1.3563
7	2	4	7	5	0	0.2153	2.4750
Sum:						1.5349	21.9978

5.1. Characteristic Polynomial

The characteristic polynomial of a matrix is defined (see refs. 9, 40) by relation: Ch(G, M, x) = det[xI - M(G)](36)

with I being the unit matrix of a pertinent order and M is a square matrix. The polynomial roots are just the **eigenvalues** of the matrix M. The string of the decreasing values of the eigenvalues is called the **spectrum** of M. The coefficients a_k of the characteristic polynomial (M = A, in which case the matrix symbol is omitted) of order N are calculable from the graph G on N vertices:

$$Ch(G, x) = \sum_{k=0}^{N} a_k(G) \cdot x^{N-k}$$
 (37)

 Relation (37) was discovered independently by Sachs, Harary, Milić, Spialter, *etc.*⁹

It makes use of the *Sachs graphs*, contained as subgraphs in *G*.
 More efficient are the numerical methods of linear algebra, such as the well-known recursive algorithms of Le Verier, Frame, or Fadeev.⁴⁰⁻⁴²

5.2. Distance Property Polynomial

A distance property polynomial was defined¹³ as:

$$P(G, M, p, x) = \sum_{k=0}^{d(G)} p(G, M, k) \cdot x^k$$
(38)

with $p(G, M, 0) = P(G) = \sum_{i} p_i$ and p_i being a vertex property.

In relation (38), p(G,M,k) is twice the contribution to the global (molecular) property P(G) of the vertex pairs located at distance k to each other, in the graph G.

The summation runs from zero to d(G), which is the *diameter* of G or the longest distance in G.

• When the local property $p_i = 1$ (*i.e.*, the vertex count), p(G,k) denotes the number of pair vertices separated by distance k in G, and the classical Hosoya polynomial⁴⁴ (more exactly twice this polynomial) is recovered. In this case, p(G,0) = N, where *N* stands for the number of vertices in the hydrogen depleted molecular graph. The polynomial coefficients p(G,M,k) are calculable as the column sums in the layer matrices LM and SM. • Thus, P(G,M,p,x) is written as P(G,LM,p,x) or P(G,SM,p,x). For example, *P*(*G*,*SUCJ*,*ch*,*x*) reads: the polynomial of the shell of unsymmetric Cluj matrix, calculated by partial charges. When p_i is 1, it can be omitted.

5.3. Global Descriptors from Polynomials

1. The sum of absolute values of the polynomial coefficients (see the Hosoya's Z-counting polynomial⁴³ and also ref. 45):

$$SumP(G, x) = \sum_{k} \left| a_{k}(G, x) \right|$$
⁽⁴⁰⁾

2. The maximal and minimal values of a spectrum (see the first eigenvalue of A, proposed by Lovasz and Pellikan⁴⁶ for characterizing the branching of a graph, and also ref. 47):

$$MaxSpP(G, x) \quad ; \quad MinSpP(G, x) \tag{41}$$

Examples are given in Table 16.

3. A *distance-extended property* can be calculated by evaluating the *first derivative* of the polynomial, for x = 1:

$$P'(G, M, p, 1) = \sum_{k=1}^{d(G)} k \cdot p(G, M, k) = D_P(G)$$
(39)

In case $p_i = 1$, is just the Wiener index.

The property p_i can be taken either as a crude property (*i.e.*, the column zero in LM) or within some weighting scheme (*i.e.*, transformed by the sequence: W-operator $W_{(M1,M2,M3)}$, W(M) matrix, LM/SM), as shown above. Any square matrix can be used as an info matrix for the layer matrices, thus resulting an unlimited number of property polynomials.

Table 16.

Distance Matrix **D**, Shell of Distance Matrix **SD**, Polynomials, Roots, **MaxSpP(G,x)** and **MinSpP(G,x)**, and **SumP(G,x)** (in bold).

D_e								SD _e							
								x _i	k	0	1	2	3	4	Real x_i
1	0	1	2	3	4	2	3	13.635		1	1	4	6	4	-0.044
2	1	0	1	2	3	1	2	-0.432		1	3	4	3	0	-0.044
3	2	1	0	1	2	2	1	-0.665		1	3	6	0	0	-0.813
4	3	2	1	0	1	3	2	-1.309		1	2	4	6	0	-0.813
5	4	3	2	1	0	4	3	-2.000		1	1	2	6	8	
6	2	1	2	3	4	0	3	-3.006		1	1	4	6	4	
7	3	2	1	2	3	3	0	-6.223		1	1	4	9	0	
SumP(G,x)								6041		7	12	28	36	16	99

 $Ch(G,D,x) = x^{7} - 120x^{5} - 752x^{4} - 1840x^{3} - 2080x^{2} - 1056x - 192$

 $P(G,SD,x) = 16x^4 + 36x^3 + 28x^2 + 12x + 7$

6. ACTIVITY PREDICTION BY CLUJ-SIMIL PROGRAM

- *Similarity* expresses the relatedness of two molecules, with a large number if their molecular descriptions are closely related and with a number going to zero in case they are unrelated.
- Dissimilarity also expresses the relatedness of two molecules, but the number goes to zero when their molecular descriptions are closely related.
- A dissimilarity measure is the well-known *chemical distance*.
- Similarity and dissimilarity are both included in the more general term *proximity*. Several proximity numbers are known but we limit here to some more utilised ones.

ACTIVITY PREDICTION BY CLUJ-SIMIL PROGRAM

6.1 Similarity Measures

Distance indices usually assume a Minkowski metric within an *m*-dimensional space:^{1,40,41}

$$D(x, y) = \left[\sum_{i=1}^{m} |x_i - y_i|^z\right]^{1/z}$$
(42)

where $x = (x_1, x_2, ..., x_m)$ and $y = (y_1, y_2, ..., y_m)$ are the two structures of *m* points. Such indices are extensively used owing to their geometrical interpretation:

-when z = 1, the city-block distance (Tanimoto or the Manhattan distance) -when z = 2, the Euclidean distance results.

Similarity Measures

Similarity indices:

1. Carhart index:⁴

$$SIM(A,B) = \sum_{k} \min(I_{Ak}, I_{Bk}) / 0.5[\sum_{k} I_{Ak} + \sum_{k} I_{Bk}]$$
(43)

where I_{Ak} are numbers describing molecule A and summation runs over all the *k* descriptors taken in work.

SIM(A,B) takes values from 0.0 (nothing in common) to 1.0 (identity).
Similarity Measures

Similarity indices:

2. Good index^{5,6} (linear form)

$$SIM(A,B)_{k} = 1 - \left(\frac{\left|I_{Ak} - I_{Bk}\right|}{\max\left|I_{Ak}, I_{Bk}\right|}\right)$$

taking values in the range [0,1].

Considering all the *nk* descriptors, the index will be:

$$SIM(A, B) = \frac{1}{w_k n} \sum_{k=1}^n w_k SIM(A, B)_k$$
 (45)

where wk is the weighting factor for the descriptor k.

(44)

Similarity Measures

Similarity indices:

3. Cluj-Simil Index (a modiffication of the Good index):

$$SIM(A,B)_{k} = 1 - \left(\frac{\left|I_{k}^{2}(A) - I_{k}^{2}(B)\right|}{I_{k}^{2}(A) + I_{k}^{2}(B)}\right)$$
(46)

Comercial programs for similarity search: CONCORD (University of Texas at Austin and TRIPOS Associates), ChemModel (Chemical Design Ltd.), ALLADIN, etc.

Similarity Measures

Any proximity measure is a metric if it satisfies the relations: ³

(1) D(x,y) = 0 for x = y; (2) D(x,y) = D(y,x) and (3) $D(x,z) \le D(x,y) + D(y,z)$

(47)

Similarity procedures provide partitioning of sets of molecules into disjoint subsets or clusters based on their similarity.

6.2. Similarity Search by Cluj-Simil Program

- Similarity search, using topological descriptors proved to be very useful in mining large databases.
- There exist global properties (i.e., properties involving the whole molecule) that do not need the speciffication of a substructure responsible for them (in the opposition to some particular biological activities).
- Many physico-chemical properties (of industrial importance), such as: boiling point, enthalpy of formation, octane number, viscosity, etc. can be estimated by using appropriate correlation equations, calibrated on well-defined training sets.
 A property similarity procedure looks for similar molecular descriptors in lists of molecules in a database.

 The software Cluj-Simil, Rel. 1.0 is written (in Delphi 4.0 language) for similarity search in large databases.

The Program has 3 modules:

- Topological index calculation (Indices)
- Similaritaty search (Simil)
- Statistical analysis (Statistics)

Cluj-Simil Program

	Similar	r ity - <u>E</u> dit	[Form1] Indices	<u>S</u> imil	Statistic	<u>W</u> indow	<u>H</u> elp						_	
			X Ba		88									
	Form1													
101200														
N I WARRANT M								т	1					
								T						
ſ														1.
				Figu	ire 8. Tl	he main	windo	w of th	e Cluj	-Simil	progra	m		

Similarity search by our program, in a set of 100 anthranylic acids (G_3), showing aniinflamatory activity (Table 17):⁴⁵⁻⁴⁷



The biological activitaty *A* was calculated from the Minimal Effective Dose MED (mg/kgbody) by formula:

$$A = \log(k / MED); \quad k = 4000$$
 (48)

TABLE 17. ANTHRANYLIC ACIDS WITH ANTIINFLAMATORY ACTIVITY

Molecule	X ₁	X ₂	X ₃	X ₄	X ₅	MED	A _{obs}
1	Н	Н	Н	Н	Н	200	1.3010
2	Н	CF ₃	Н	Н	Н	3.3	3.0835
3	Н	CH ₃	Н	Н	Н	100	1.6021
4	Н	Cl	Н	Н	Н	25	2.2041
5	Н	NH ₂	Н	Н	Н	400	1.0000
6	Н	OCH ₃	Н	Н	Н	50	1.9031
7	Н	SO ₂ N(CH ₃) ₂	Н	Н	Н	50	1.9031
8	Н	COCH ₃	Н	Н	Н	200	1.3010
9	Н	N(CH ₃) ₂	Н	Н	Н	100	1.6021
10	Н	Н	Cl	Н	Н	200	1.3010

TABLE 17. ANTHRANYLIC ACIDS WITH ANTHINFLAMATORY ACTIVITY

11	Н	C ₄ H ₉	Н	Н	Н	200	1.3010
12	Н	CN	Н	Н	Н	25	2.2041
13	Н	C ₃ H ₇	Н	Н	Н	50	1.9031
14	Н	SCH ₃	Н	Н	Н	100	1.6021
15	Н	NO ₂	Н	Н	Н	100	1.6021
16	Н	OC ₂ H ₅	Н	Н	Н	100	1.6021
17	Н	Br	Н	Н	Н	50	1.9031
18	Н	C ₂ H ₅	Н	Н	Н	25	2.2041
19	Cl	Н	Н	Н	Н	50	1.9031
20	CH ₃	Н	Н	Н	Н	200	1.3010

TABLE 17. ANTHRANYLIC ACIDS WITH ANTHINFLAMATORY ACTIVITY

	21	Н	Н	CH ₃	н	Н	400	1.0000
	22	Cl	Н	Cl	Н	Н	100	1.6021
1000	23	Н	Cl	Cl	Н	Н	100	1.6021
NULL N	24	CH ₃	CH ₃	Н	Н	Н	10.4	2.5850
THE PARTY	25	CH ₃	CF ₃	Н	Н	Н	1	3.6021
	26	CH ₃	SO ₂ N(CH ₃) ₂	Н	Н	Н	6.2	2.8097
	27	CH ₃	NH ₂	Н	Н	Н	50	1.9031
	28	CH ₃	N(CH ₃) ₂	Н	Н	Н	6.2	2.8097
	29	CH ₃	Cl	Н	Н	Н	5.3	2.8778
	30	CH ₃	OCH ₃	Н	Н	Н	6.2	2.8097

TABLE 17.ANTHRANYLIC ACIDS WITH ANTIINFLAMATORY ACTIVITY

	31	Н	CF ₃	Н	CF ₃	Н	100	1.6021
	32	Br	CF ₃	Н	Н	Н	1.6	3.3979
NA C	33	Br	Br	Н	Н	Н	3.1	3.1107
W.L.	34	Н	CH ₃	Н	CH ₃	Н	100	1.6021
THE CA	35	Cl	Н	Н	Н	CH ₃	12.5	2.5051
11.14	36	Br	CN	Н	Н	Н	1.5	3.4260
	37	F	Cl	Н	Н	Н	3.1	3.1107
	38	Н	Cl	Н	Cl	Н	50	1.9031
	39	Cl	Cl	Н	Н	Н	2.1	3.2798
	40	CH ₃	NO ₂	Н	Н	Н	3.1	3.1107

TABLE 17. ANTHRANYLIC ACIDS WITH ANTHINFLAMATORY ACTIVITY

	41	CH ₃	CN	Н	Н	Н	3.1	3.1107
	42	CH ₃	C ₂ H ₅	Н	Н	Н	3.1	3.1107
NU-	43	Cl	Н	Н	Н	Cl	3.1	3.1107
WALKS	44	Cl	CH ₃	Н	Н	Н	6.2	2.8097
THE PARTY	45	Cl	Н	Н	Cl	Н	12.5	2.5051
100	46	CH ₃	Н	Н	Н	CH ₃	50	1.9031
	47	CH ₃	Н	Н	CH ₃	Н	200	1.3010
	48	Н	CH ₃	CH ₃	Н	Н	200	1.3010
	49	CH ₃	Н	CH ₃	Н	Н	400	1.0000
	50	CH ₃	SO ₂ N(CH ₃) ₂	Н	Н	Cl	0.7	3.7570

TABLE 17. ANTHRANYLIC ACIDS WITH ANTIINFLAMATORY ACTIVITY

	51	Cl	Cl	Н	Cl	Н	3.1	3.1107
	52	Н	Cl	Cl	Cl	Н	200	1.3010
1111	53	CH ₃	CH ₃	Н	CH ₃	Н	25	2.2041
Null Sh	54	CH ₃	Н	CH ₃	CH ₃	Н	100	1.6021
THE P	55	Н	Cl	CH ₃	Cl	Н	100	1.6021
	56	CH ₃	Н	CH ₃	Н	CH ₃	400	1.0000
	57	Cl	SO ₂ N(CH ₃) ₂	Н	Н	Cl	1.3	3.4881
	58	Cl	OCH ₃	Н	Н	Cl	0.3	4.1249
	59	CH ₃	Br	Н	Н	CH ₃	1.6	3.3979
	60	Cl	CN	Н	Н	Cl	1.6	3.3979

TABLE 17. ANTHRANYLIC ACIDS WITH ANTHINFLAMATORY ACTIVITY

	61	CH ₃	Cl	Н	Н	Cl	3.1	3.1107
	62	CH ₃	Cl	Н	Н	CH ₃	0.4	4.0000
NUM I	63	Cl	OC ₂ H ₅	Н	Н	Cl	0.8	3.6990
WALKS	64	CH ₃	COCH ₃	Н	Н	CH ₃	0.9	3.6478
TANK D	65	CH ₃	N(CH ₃) ₂	Н	Н	CH ₃	1.6	3.3979
1414	66	C ₂ H ₅	NO ₂	Н	Н	C ₂ H ₅	12.5	2.5051
	67	NH ₂	Cl	Н	Н	CH ₃	25	2.2041
	68	CH ₃	CH ₃	Н	Cl	Н	25	2.2041
	69	CH ₃	CN	Н	Н	CH ₃	0.4	4.0000
	70	CH ₃	SCH ₃	Н	Н	CH ₃	0.4	4.0000

TABLE 17. ANTHRANYLIC ACIDS WITH ANTIINFLAMATORY ACTIVITY

	71	CH ₃	NO ₂	Н	Н	Cl	1.6	3.3979
	72	CH ₃	C ₃ H ₇	Н	Н	CH ₃	6.2	2.8097
111111	73	C ₂ H ₅	SO ₂ N(CH ₃) ₂	Н	Н	C ₂ H ₅	12.5	2.5051
TWWIT I	74	C ₂ H ₅	COCH ₃	Н	Н	C ₂ H ₅	25	2.2041
10.11	75	Cl	Н	CF ₃	Н	Cl	0.8	3.6990
	76	CH ₃	SO ₂ N(CH ₃) ₂	Н	Н	CH ₃	0.5	3.9031
	77	CH ₃	NH ₂	Н	Н	Cl	6.2	2.8097
	78	CH ₃	CH ₃	Н	Н	Cl	12.5	2.5051
	79	Cl	Cl	Н	Н	CH ₃	0.8	3.6990
	80	Cl	Н	C ₂ H ₅	Н	Cl	0.8	3.6990

TABLE 17. ANTHRANYLIC ACIDS WITH ANTIINFLAMATORY ACTIVITY

	81	Cl	Н	Cl	Cl	Н	400	1.0000
	82	Cl	Cl	Cl	Н	Н	200	1.3010
	83	Cl	Н	Cl	Н	Cl	100	1.6021
Walker	84	NH ₂	CH ₃	Н	Н	CH ₃	25	2.2041
THE P	85	CH ₃	CH ₃	Н	Н	CH ₃	6.2	2.8097
1111	86	Cl	CH ₃	Н	Н	CH ₃	3.1	3.1107
	87	CH ₃	Cl	Н	CH ₃	Н	1.6	3.3979
N. P. M.	88	CH ₃	C_2H_5	Н	Н	CH ₃	1.6	3.3979
	89	CH ₃	NH ₂	Н	Н	Cl	1.3	3.4881
	90	CH ₃	SO ₂ CH ₃	Н	Н	CH ₃	0.6	3.8239

TABLE 17. ANTHRANYLIC ACIDS WITH ANTHINFLAMATORY ACTIVITY

	91	Cl	N(CH ₃) ₂	Н	Н	Cl	0.6	3.8239
	92	CH ₃	SOCH ₃	Н	Н	CH ₃	0.5	3.9031
1111	93	Cl	Cl	Cl	Н	CH ₃	12.5	2.5051
Null S	94	CH ₃	CH ₃	Н	CH ₃	CH ₃	100	1.6021
TANK A	95	Cl	Cl	Cl	Н	Cl	12.5	2.5051
1.1.1	96	Cl	CH ₃	Cl	Н	Cl	12.5	2.5051
	97	Cl	Cl	Cl	Cl	Н	100	1.6021
	98	Cl	Cl	Н	Cl	Cl	1.6	3.3979
	99	Cl	Cl	Cl	Cl	Cl	25	2.2041
	100	CH ₃	CH ₃	Cl	CH ₃	Cl	100	1.6021

Table 18. Literature Data:47

No.	X ₁	X ₂	X ₃	X ₄	X ₅	A	calc	A _{obs}
						Р	С	
1	CH ₃	NH ₂	Н	Н	CH ₃	2,121	2,784	1,903
2	CH ₃	OCH ₃	Н	Н	Cl	3,551	3,925	3,824
3	CH ₃	CF ₃	Н	Н	CH ₃	4,121	4,156	3,699
4	CH ₃	NO ₂	Н	Н	CH ₃	3,308	2,457	3,398
5	CH ₃	Cl	Н	Н	NH ₂	2,409	2,731	2,810
6	Cl	CN	Н	Н	CH ₃	3,839	4,759	3,903
7	Cl	N(CH ₃) ₂	Н	Н	CH ₃	3,625	3,463	3,398
8	CH ₃	Cl	Н	Н	Cl	3,161	3,448	3,699
9	Cl	Cl	Н	CH ₃	Н	2,891	2,290	2,810
10	CH ₃	Cl	Н	Cl	Н	2,728	2,634	3,398

The prediction quality by PRECLAV ($R^2 = 0.7026$, $r_k = 0.7333$) was considered as "good" while those supplied by CODESSA ($R^2 = 0.4254$, $r_k = 0.6444$) as "satisfactory".

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6.3. Cluj-Simil Algorithm.48

- Separate the initial set in two subsets: the training set and the prediction set. (In our example, the 100 molecules were partitioned in 1:1 ratio).
- Calculate topological descriptors for all molecules of the two sets.
- 3. Clustering the training set in m (here m = 4) *clusters*,
 - with optional leaders and similarity criteria, as follows:

•	a.	leader with	$A_{obs} \sim 1$	(molecule # 5)
•	b.	leader with	$A_{obs} \sim 2$	(molecule # 6)
•	C.	leader with	$A_{obs} \sim 3$	(molecule # 2)
	-	I a a la a suddha	A 4	(max] = max

- d. leader with $A_{obs} \sim 4$ (molecule #70)
- A unique chriterion was used in our example: index DSI.

- 4. Calculate regression equations (mono or bivariate) in the clusters of training set.
- Here, the modeling descriptors were different from the similarity criterion: namely, Cluj indices, centrality indices and composite indices calculated by the aid of Walk Matrix operator. Some of these descriptor take into account the heteroatom and multple bond present in molecule.
- Regressions were calculated by MATLAB: STATISTIC TOOLBOX, REGRESS.
 - **5.** Clustering the prediction set. The step 2 is repeated, with the same leaders and similarity criterion as used for the training set.
- 6. Predict the property A by the aid of regression equations, calibrated in step 4.
 - **7. Validate the algorithm** (in case the activity in the predicting set was known).
 - Reslts of the application of the above algorithm are given in Tables 19-22 (only the prediction step).

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6.4. Study of the Case: Antiinflamatory Activity of Anthranylic Acids

Cluster (a); Leader #5.

THE EQUATION USED FOR PREDICTION (TABLE 19) IS THAT CALIBRATED IN THE TRAINING CLUSTER (A):

$$\lg Med_{pr} = -1.4 \cdot 10^{-3} \cdot CjDiIP + 3.3 \cdot 10^{-3} \cdot CFDeIP$$
(49)
 $n = 7; \ R^2 = 0.9991$

where *CJDiIP* and *CFDeIP* are the theoretical hyper-indices *CJDi* and *CFDe* and *n* is the number of structures in the cluster.

Table 19. Prediction in Cluster (a); Leader #5

Molecule	X ₁	X ₂	X ₃	X ₄	X ₅	A _{obs}	A _{calc}
21	Н	Н	CH ₃	Н	Н	1.000	1.207
3	Н	CH ₃	Н	Н	Н	1.602	1.739
37	F	Cl	H	H	H	3.111	2.825
38	Н	Cl	Н	Cl	Н	1.903	1.866
22	Cl	Н	Cl	Н	Н	1.602	2.211
23	Н	Cl	Cl	Н	Н	1.602	1.540
39	Cl	Cl	Н	Н	Н	3.280	2.825

3.500 y = 1.2808x - 0.5864 $R^2 = 0.8759$ 3.000 2.500 A obs 2.000 1.500 1.000 0.500 1.000 1.200 1.600 2.000 1.400 1.800 2.200 2.400 2.600 2.800 3.000 A pred

Figure 9. The plot A_{obs} vs. A_{calc} (cf. eq. 49)

The quality of prediction is good (R2 = 0.8759), as can be seen in the plot $A_{obs} vs. A_{cale}$ (Figure 9). This fortunate case, when the activity of the structures in the prediction set is known, can be considered the validation step of the algorithm.

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Prediction step

Cluster (b); Leader #6.

THE EQUATION USED FOR PREDICTION (TABLE 20) IS THAT CALIBRATED IN THE TRAINING CLUSTER (B):

$$\lg Med_{pr} = 69.5201 \cdot CCH - 6 \cdot 10^{-3} \cdot XCH$$
(50)

 $n = 8; R^2 = 0.9813$

where *CCH* and *XCH* are the centrality and centrocomplexity indices, respectively, weighted by the partial charges of atoms or of *hydride groups*.

Table 20. Prediction in Cluster (b); Leader #6

Molec	ule	X ₁	X ₂	X ₃	X ₄	X ₅	A _{obs}	A _{calc}
14		Н	SCH ₃	Н	Н	Н	1.602	1.578
27		CH ₃	NH ₂	Н	Н	Н	1.903	1.908
47		CH ₃	Н	Н	CH ₃	Н	1.301	1.778
9		Н	N(CH ₃) ₂	Н	Н	Н	1.602	1.697
8		Н	COCH ₃	Н	Н	Н	1.301	1.564
67		NH ₂	Cl	Н	Н	CH ₃	2.204	2.370
68		CH ₃	CH ₃	Н	Cl	Н	2.204	2.117
78		CH ₃	CH ₃	Н	Н	Cl	2.505	2.761



Figure 10. The plot A_{obs} vs. A_{calc} (cf. eq. 50)

The quality of prediction is again good ($R^2 = 0.829$ - Figure 10).

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Prediction step

Cluster (c); Leader #2.

THE EQUATION USED FOR PREDICTION (TABLE 21) IS THAT CALIBRATED IN THE TRAINING CLUSTER (C):

$$\lg Med_{pr} = 3.46 \cdot 10^{-2} \cdot CjDeIE - 5.4 \cdot 10^{-3} \cdot W_{CjD,Di,A}$$
(51)

 $n = 10; R^2 = 0.9272$

where *CJDeIE* is the Cluj Detour index (calculated on edges) while $W_{CJDiDiA}$ is the index obtained by the matrix operator $W_{(M1,M2,M3)}$ with $M_1 = CJD$ (matrix Cluj-Distance),

 $M_2 = Di$ (distance matrix) and $M_3 = A$ (adjacency matrix).

Similarity by Cluj-Simil Program

Table 21. Prediction in Cluster (c); Leader #2

	Molecule	X ₁	X ₂	X ₃	X ₄	X ₅	A _{obs}	A _{calc}
	95	Cl	Cl	Cl	Н	Cl	2.505	2.451
-	93	Cl	Cl	Cl	Н	CH ₃	2.505	2.451
NUM.	96	Cl	CH ₃	Cl	Н	Cl	2.505	2.451
	80	Cl	Н	C ₂ H ₅	Н	Cl	3.699	3.472
	88	CH ₃	C ₂ H ₅	Н	Н	CH ₃	3.398	3.686
	53	CH ₃	CH ₃	Н	CH ₃	Н	2.204	2.002
	85	CH ₃	CH ₃	Н	Н	CH ₃	2.810	3.061
	77	CH ₃	NH ₂	Н	Н	Cl	2.810	3.061
	55	Н	Cl	CH ₃	Cl	Н	1.602	1.120
	52	Н	Cl	Cl	Cl	Н	1.301	1.120



Figure 11. The plot A_{obs} vs. A_{calc} (cf. eq. 51)

The quality of prediction is the best, in our experiment: $R^2 = 0.9438$ (Figure 11).

Prediction step

Cluster (d); Leader #70.

THE EQUATION USED FOR PREDICTION (TABLE 21) IS THAT CALIBRATED IN THE TRAINING CLUSTER (D):

$$\lg Med_{pr} = 3.13 \cdot 10^{-2} \cdot CjDeIE - 4.8 \cdot 10^{-3} \cdot W_{CjD,Di,A}$$
(52)

 $n = 11; R^2 = 0.9596$

where *CJDeIE* is the Cluj Detour index (calculated on edges) while $W_{CJDiDiA}$ is the index obtained by the matrix operator $W_{(M1,M2,M3)}$ with $M_1 = CJD$ (matrix Cluj-Distance),

 $M_2 = Di$ (distance matrix) and $M_3 = A$ (adjacency matrix).

Table 22. Prediction in Cluster (d); Leader #70

Molecul	X ₁	X ₂	X ₃	X ₄	X ₅	A _{obs}	A _{calc}
e							
69	CH ₃	CN	Н	Н	CH ₃	4.000	3.826
80	Cl	Н	C ₂ H ₅	Н	Cl	3.699	3.633
93	Cl	Cl	Cl	Н	CH ₃	2.505	2.709
96	Cl	CH ₃	Cl	Н	Cl	2.505	2.709
95	Cl	CH ₃	Cl	Н	Cl	2.505	2.709
40	CH ₃	NO ₂	Н	Н	Н	3.111	3.856
2	Н	CF ₃	Н	Н	Н	3.084	3.328
92	CH ₃	SOCH ₃	Н	Н	CH ₃	3.903	4.191
53	CH ₃	CH ₃	Н	CH ₃	Н	2.204	2.240
85	CH ₃	CH ₃	Н	Н	CH ₃	2.810	3.192
68	CH ₃	CH ₃	Н	Cl	Н	2.204	2.240



Figure 12. The plot A_{obs} vs. A_{calc} (cf. eq. 52)

The quality of prediction is again good ($R^2 = 0.8692$ - Figure 12)

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 A reunion of the above predictions is given in Figure 13.

The global correlation : A pred VS. A obs is pretty good (R² = 0.8647), in comparison to the literature data (R² < 0.7100).⁴⁷
 Among the 50 structures in the prediction set 42 were correctly classified.

4.5 y = 0.8855x + 0.1647 $R^2 = 0.8647$ 4 3.5 3 Ĩ **sqo e** 2.5 I ĪĪ 2 Ī Ŧ 1.5 -I I Ī 1 -I 0.5 -1.5 2 2.5 3.5 3 4.5 1 4 A pred

Figure 13. The plot A_{obs} vs. A_{calc} (cf. eqs. 49-52)

7. CONCLUSIONS

- **Layer matrices** have gained a constant interest among the chemical theorists, both in correlating studies and graph discriminating analysis. It is noteworthy that the super-index EATI, authored by Hu and Xu⁴⁹ is based on a layer matrix originating at the **TOPOGROUP CLUJ**.
- The shell matrix proposed by Randić⁵⁰ in 2001 is a LeW matrix, published by us^{3,4} since 1994. We recognize here the priority of the Novosibirsk group, guided by Skorobogatov.⁵¹

Our **aim** was to contribute, along with the well-known commercial programs: CODESSA,⁵² MOLCONN Z,⁵³ DRAGON,⁵⁴ TOSS MODE⁵⁵ or POLLY,⁵⁶ by **TOPOCLUJ** software package² (which comes from an experience of two decades of our group)^{1,57} to the increase of use of the topological descriptors in modeling physico-chemical and biological properties.
7. CONCLUSIONS

- **Description of molecules** by the aid of topological indices: DSI, Cluj (CjDi, CjDe, CFDi, CFDe), $W_{(M1,M2,M3)}$, indices of centricity and centrocomplexity (weighted by partial charges of atoms and hydride groups) is adequate for the main purpose: the similarity search and QSAR.
- **Clustering** by the criterion: DSI (that weights the atom valency by group electronegativities of Sanderson type) is in agreement with the chemical percepts, in the set of Anthranylic acids.
- Ecuations calibrated within the training set showed good statistics, that recommend them for the prediction set.

7. CONCLUSIONS

- The **predicted values** for the biological activity of the structures in the prediction set are **pertinent**: the plot *A* _{pred} *vs. A* _{obs} showed a correlation: $R^2 = 0.8647$, which overpassed the results reported in literature.⁹ Among the 50 structures in the prediction set 42 were **correctly classified.**
 - Our procedure can be useful in **Combinatorial Chemistry**, for fast clustering, according to the similarity vs. selected leaders, and predicting (non-measured) molecular properties.

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