

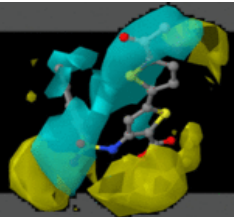
Rational Design of Potential Novel Pharmaceutical Compounds Through Computational Approaches and Machine Learning Techniques.



SAPIENZA
UNIVERSITÀ DI ROMA

PhD School of Pharmaceutical Sciences XXX Cycle
Department of Chemistry and Drug Technologies
Faculty of Pharmacy and Medicine
“Sapienza” University of Rome

Manuela Sabatino



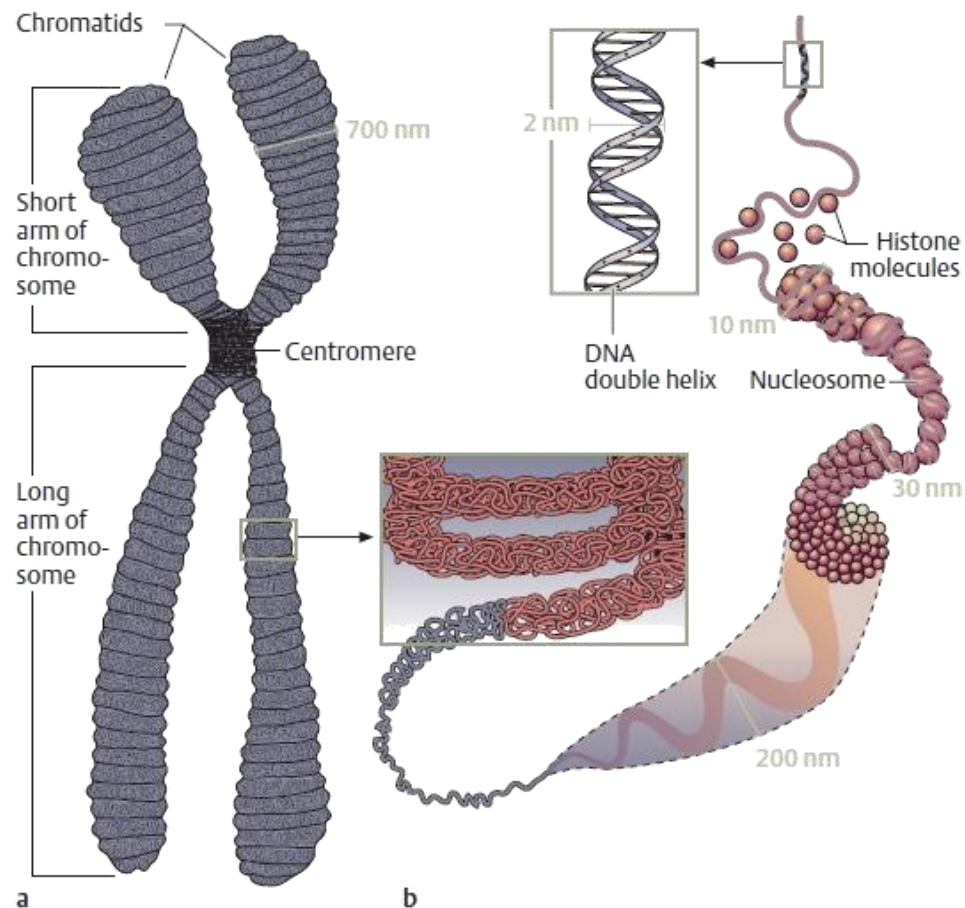
Epigenetics

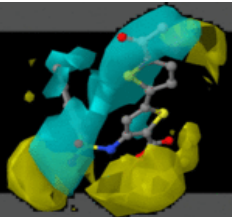
by www.rcmd.it

Filamentous Chromosomal inactivation
 Change Replication Suppressor eukaryotic Multicellular
 Differentiate code Unicellular **Epigenetics** Cell Pattern
 Abnormalities Enzyme lysine Genetic Embryonic Expression
 multigeneration I Zygote effect Amide
 Methylation Cancer

The word “epigenetic” literally means “in addition to changes in genetic sequence.”

The term has evolved to include any process that alters gene transcription without changing the DNA sequence, and leads to modifications that can be transmitted to daughter cells



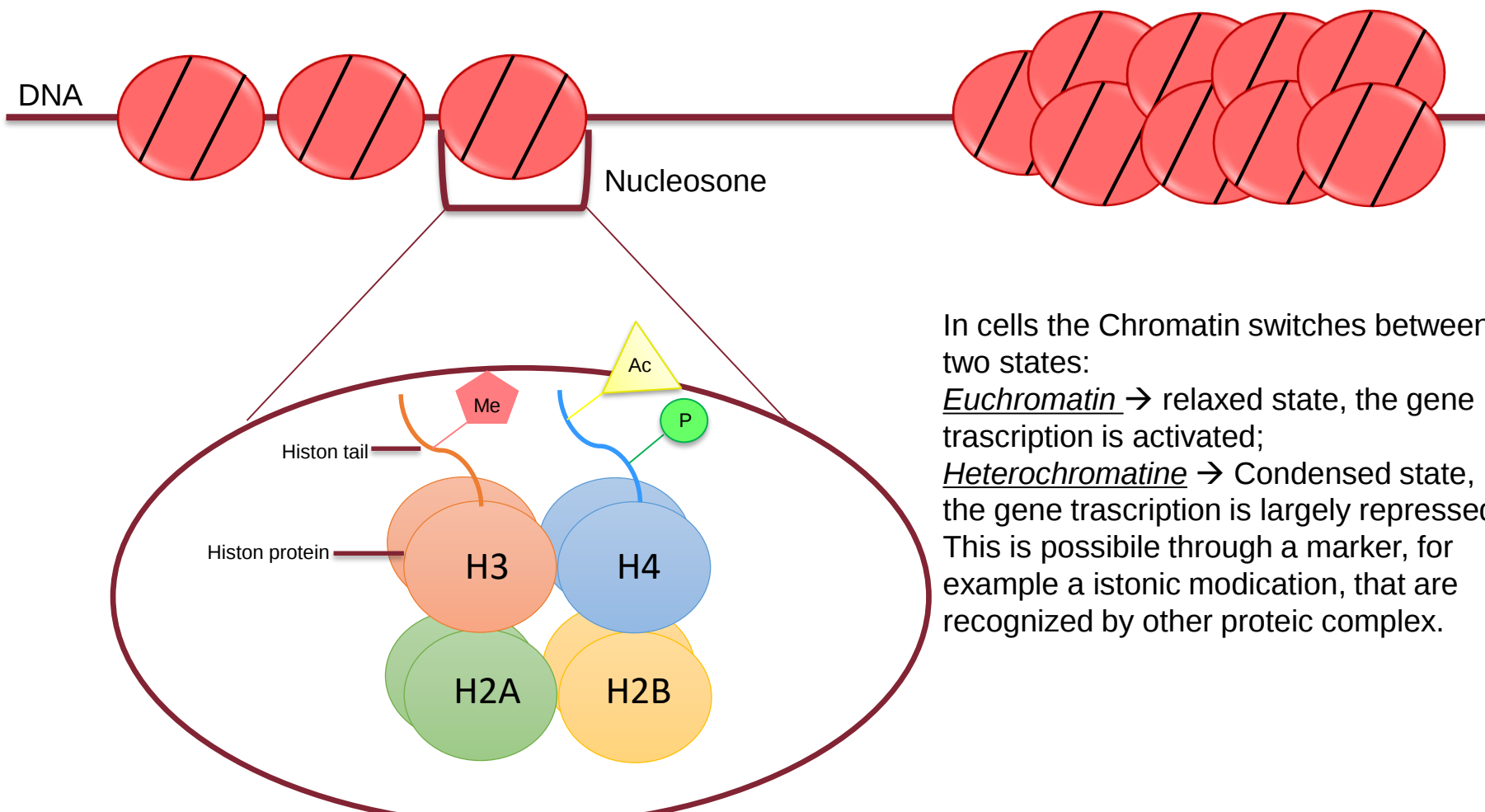


Epigenetics

by www.RCMD.it

Euchromatin

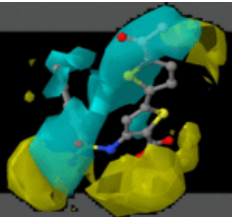
Heterochromatin



In cells the Chromatin switches between two states:

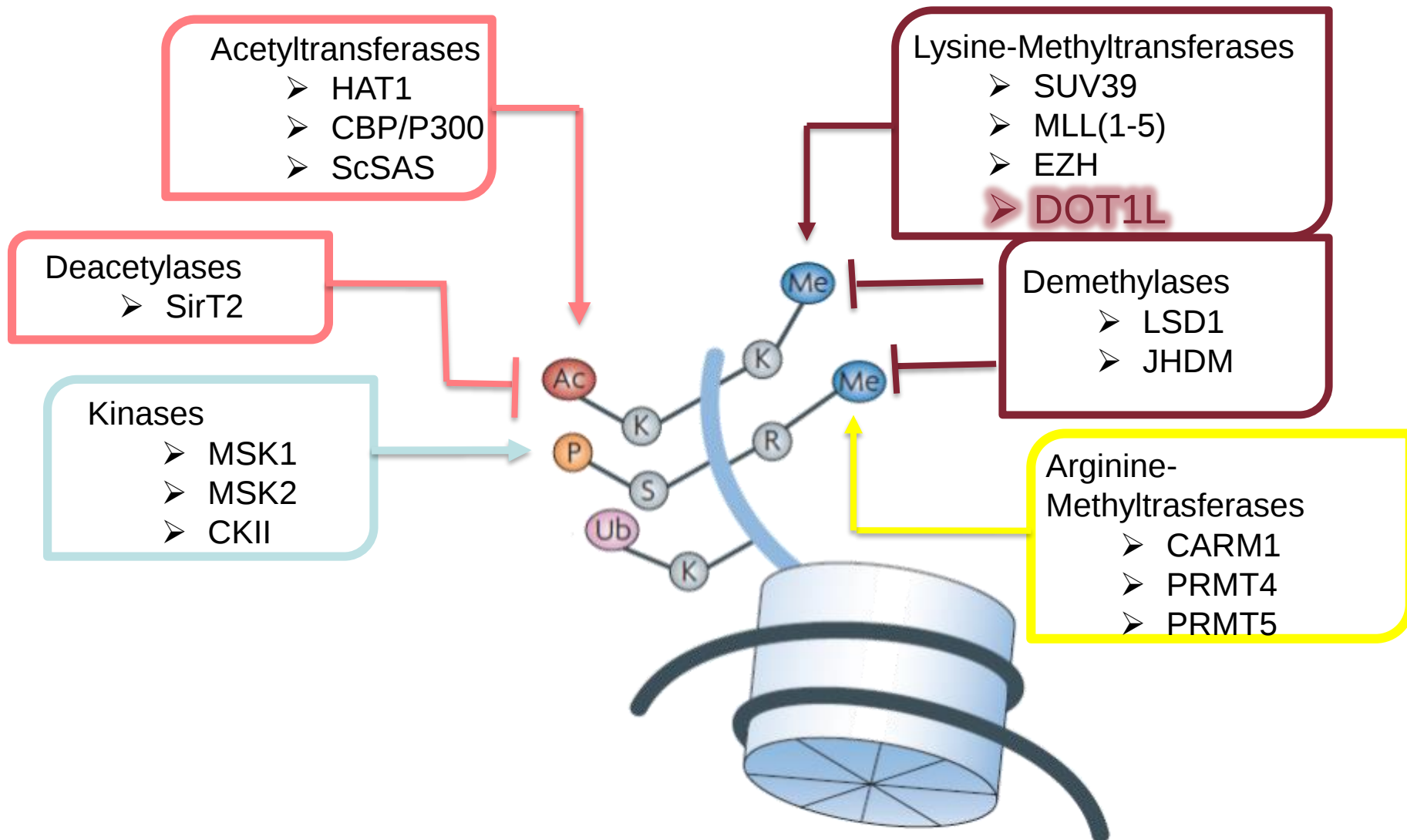
Euchromatin → relaxed state, the gene trascription is activated;

Heterochromatine → Condensed state, the gene trascription is largely repressed; This is possibile through a marker, for example a istonic modication, that are recognized by other proteic complex.



Epigenetics

by www.RCMD.it

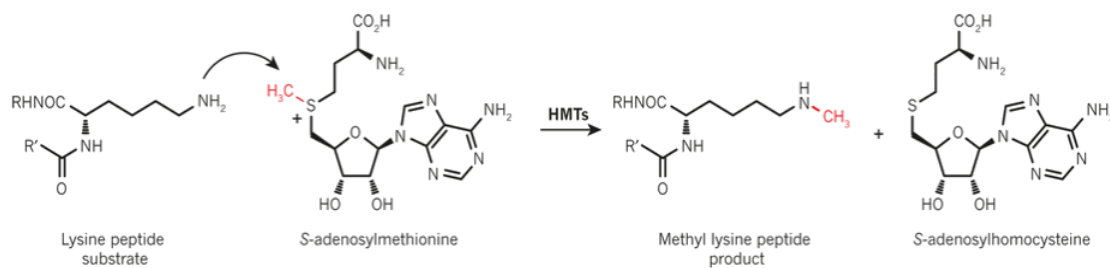
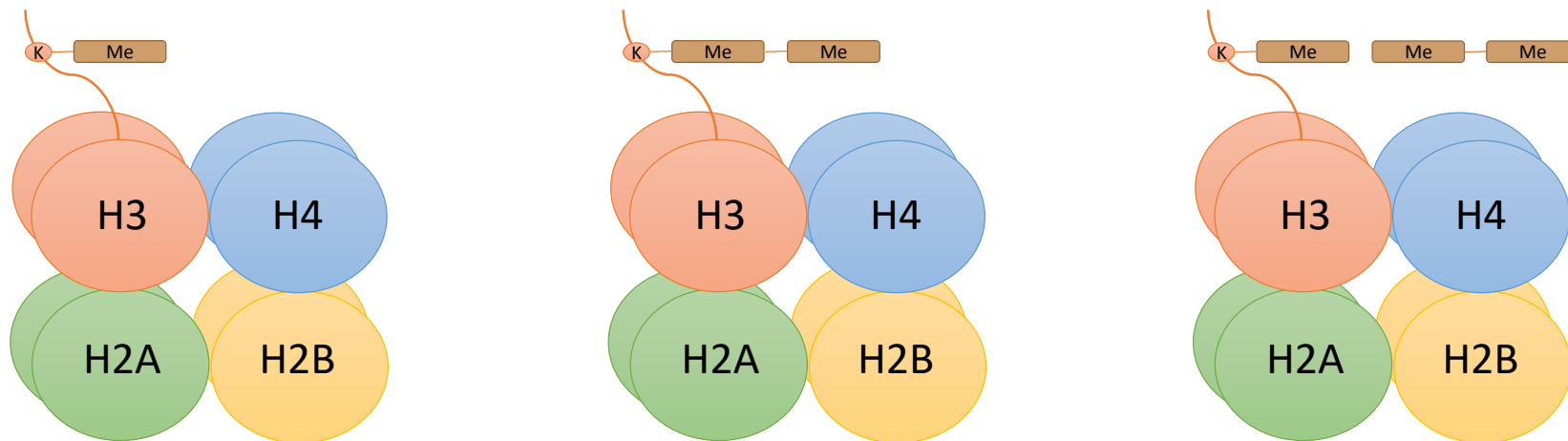




Dot1l catalytic mechanism

by www.rcmd.it

Disruptor Of Telomeric Silencing 1-Like Methyltransferase H3K79 selective



TRANSCRIPTIONAL ACTIVATIONS

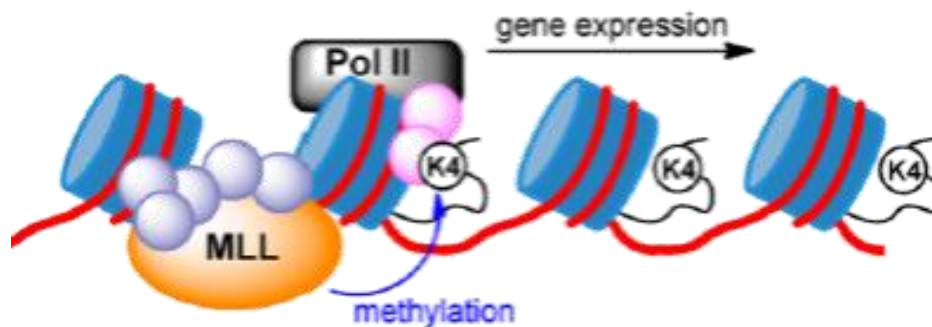


Dot1l and MLL

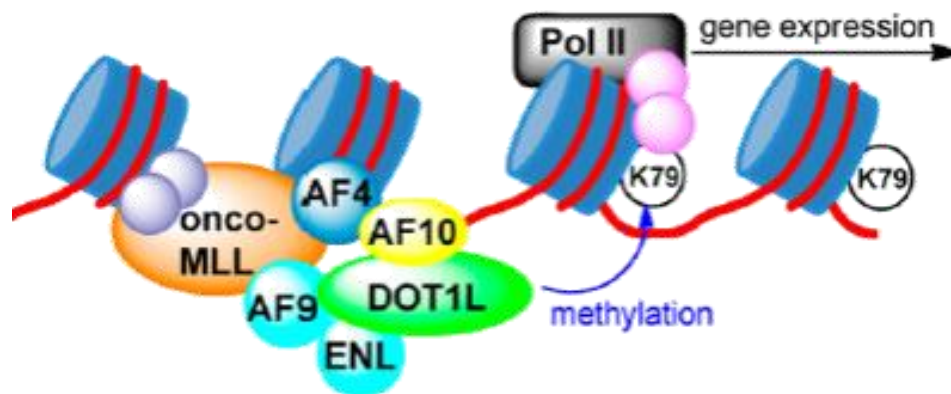
by www.RCMD.it

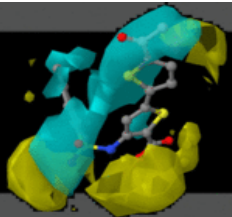
MLL is a methyltransferase and modifies the lysine 4 of the histone 3

Wild-type



**Myeloid
Lymphoid
Leukemia**





Objective Of The Study

by www.RCMD.it

DOT1L Inhibitors Study



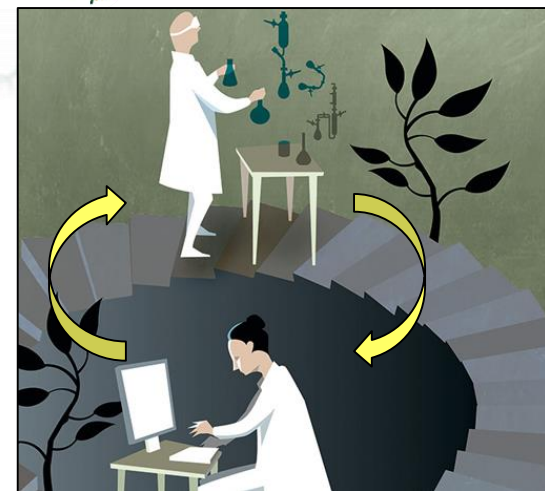
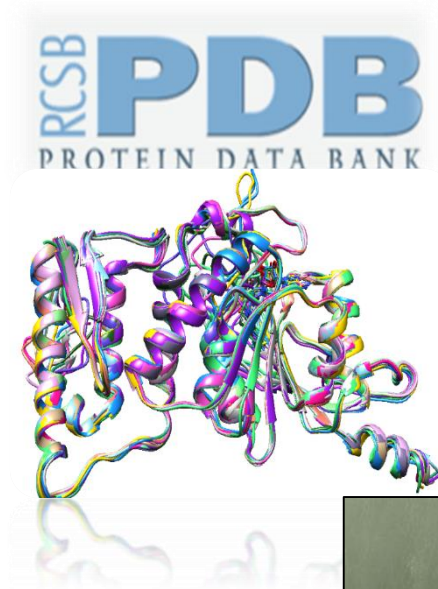
Quantitative Predictive Models

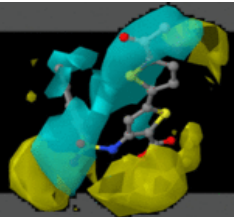


Design of New Compounds



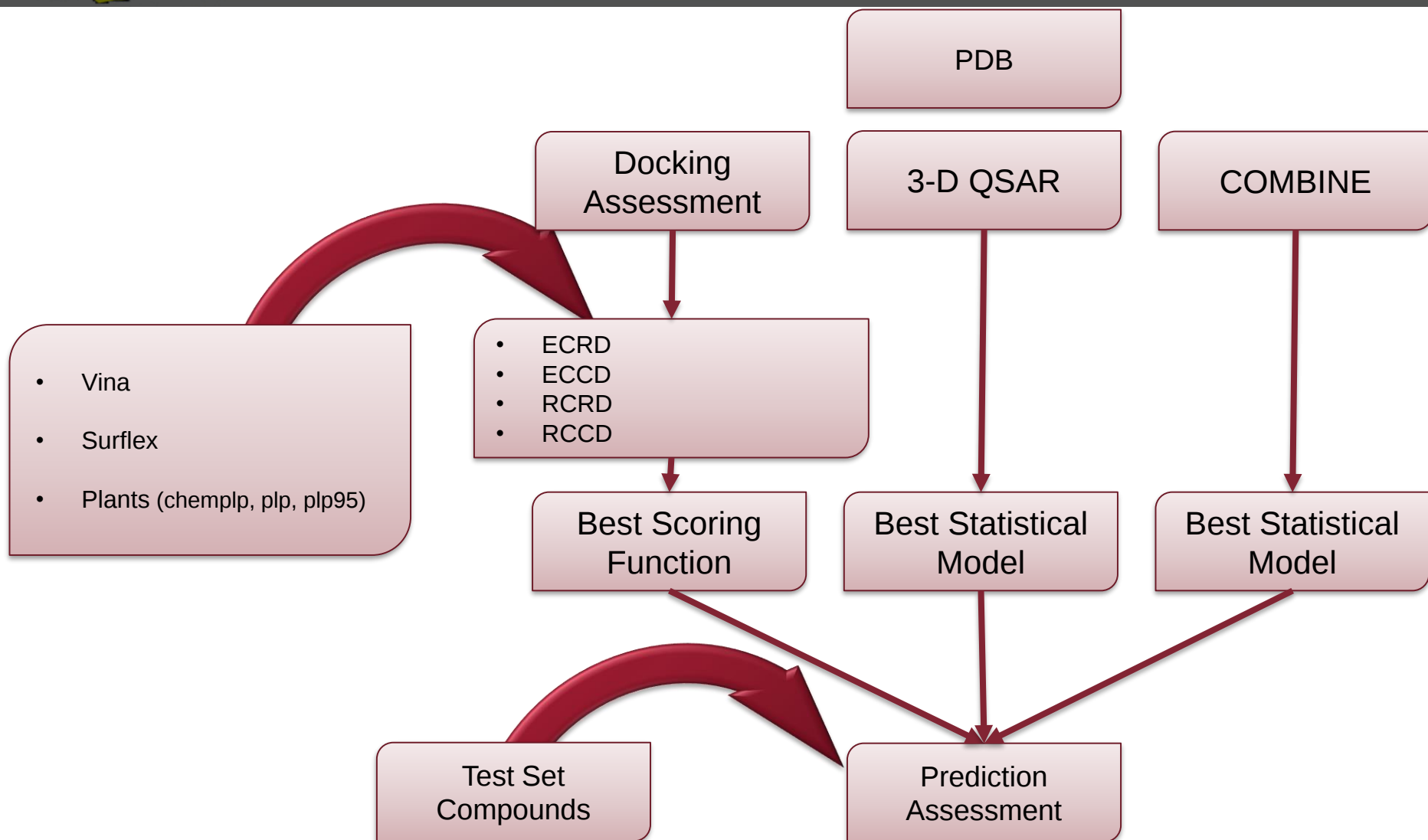
Prioritize Synthesis

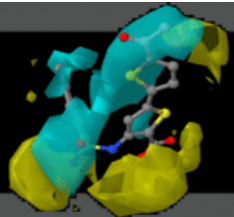




Workflow

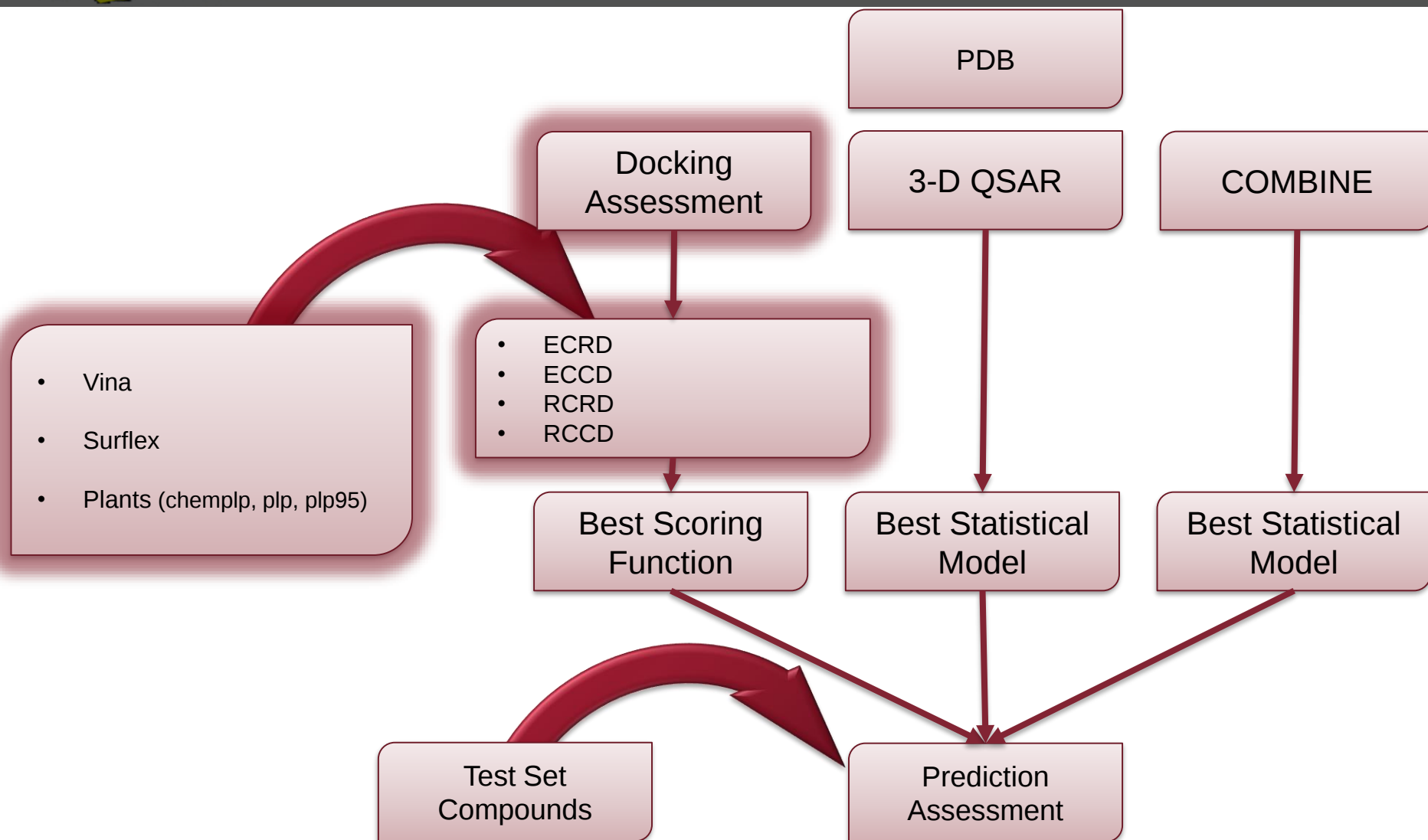
by www.RCMD.it

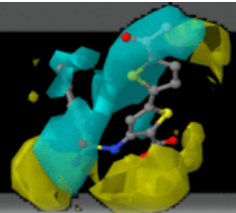




Workflow

by www.RCMD.it

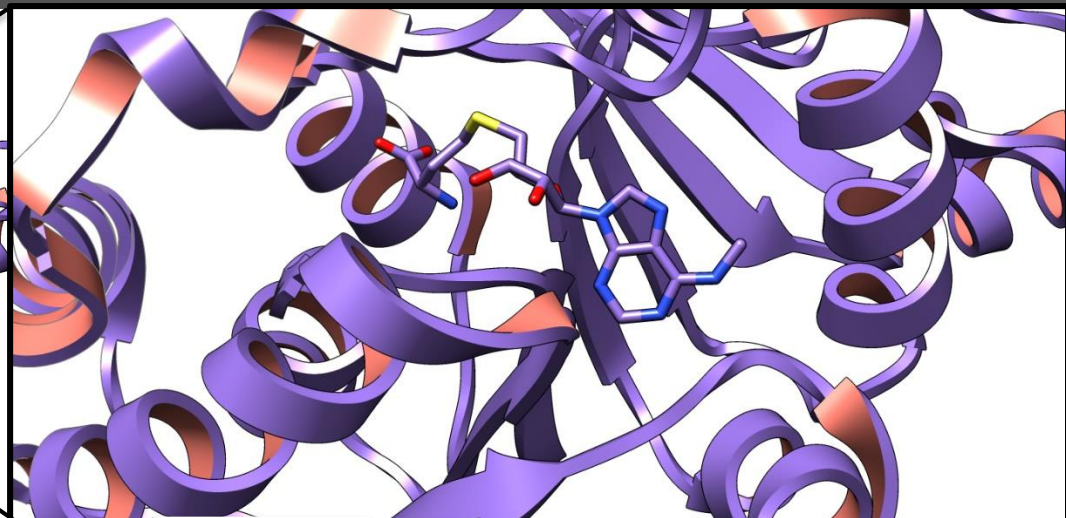
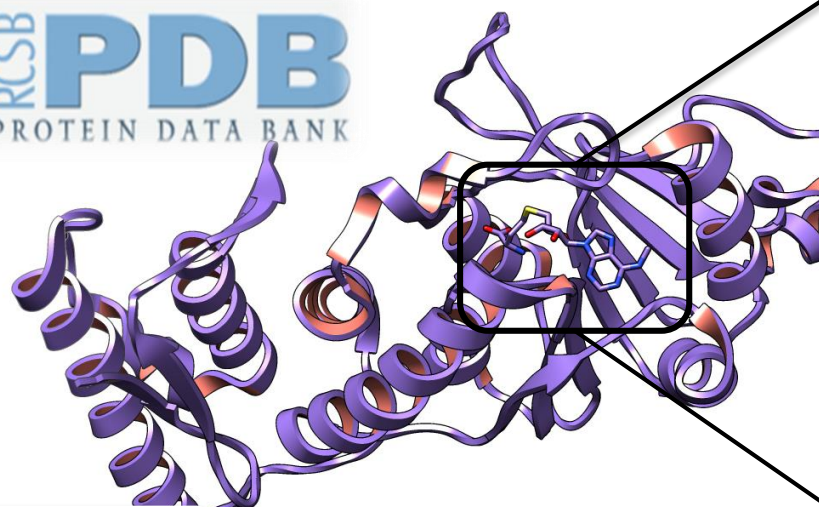




Docking Assessment

by www.rcmd.it

RCSB
PDB
PROTEIN DATA BANK



4EK9



4EKI



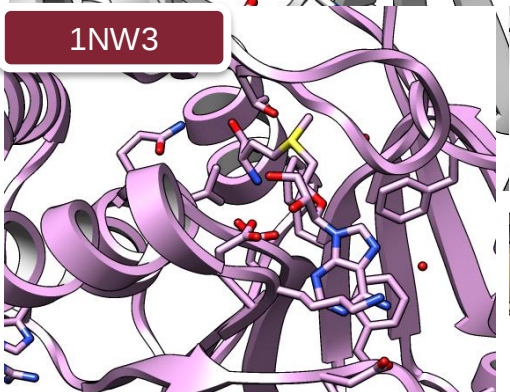
4ER0



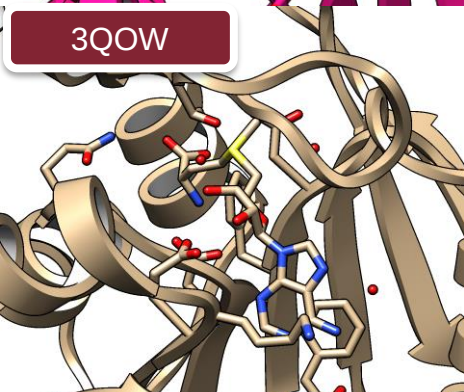
4ER5



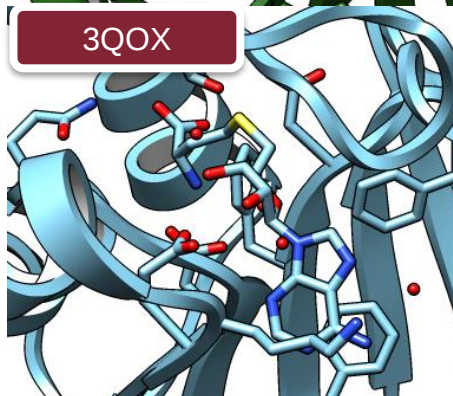
1NW3



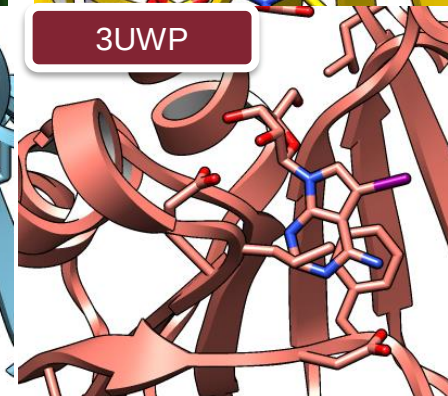
3QOW

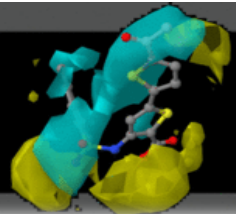


3QOX



3UWP

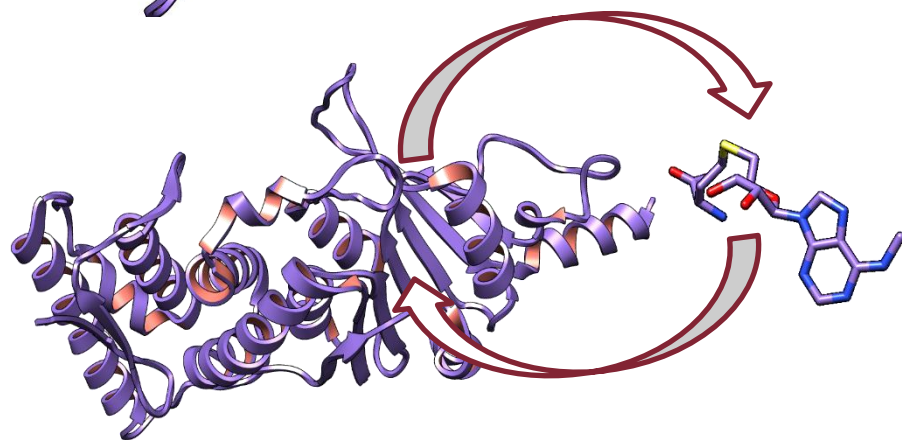
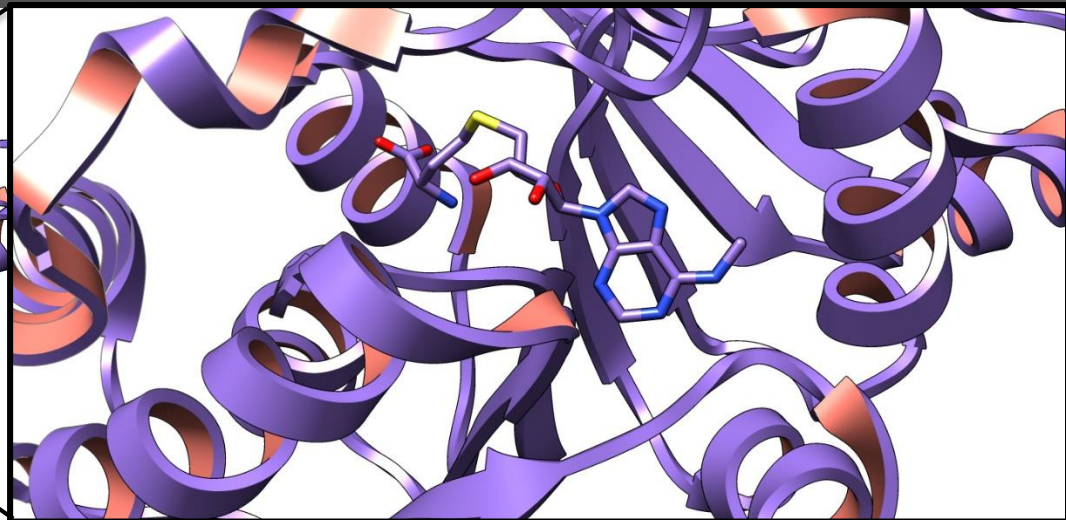




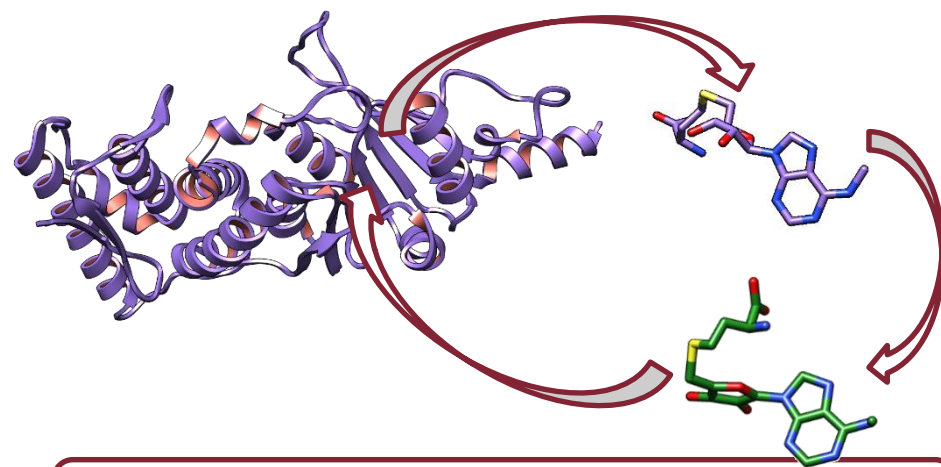
Docking Assessment

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RCSB
PDB
PROTEIN DATA BANK



Experimental Conformation Re-Docking



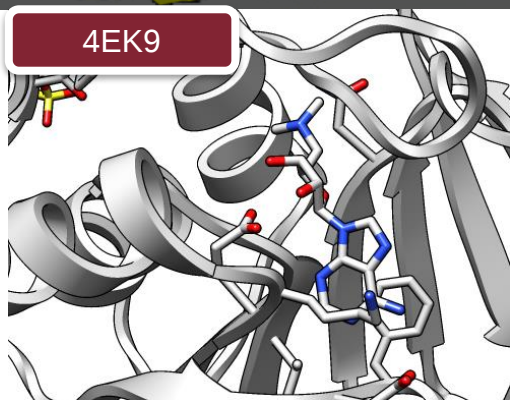
Random Conformation Re-Docking



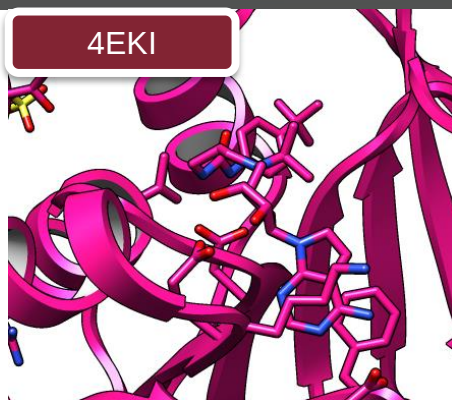
Docking Assessment

by www.RCMD.it

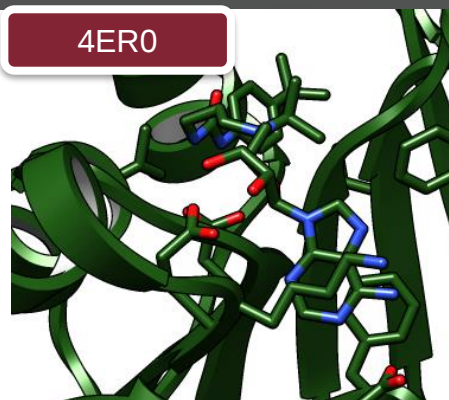
4EK9



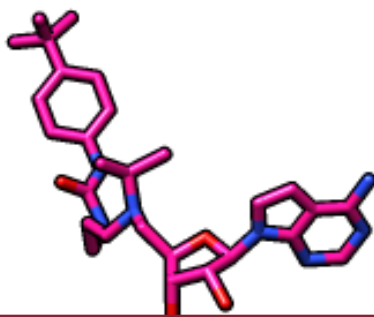
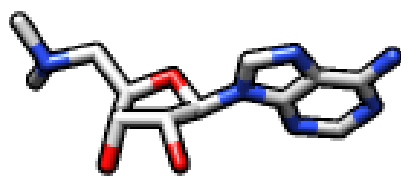
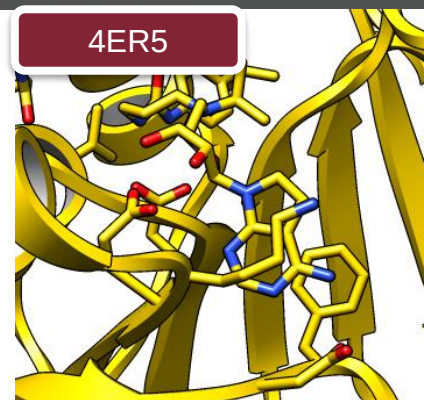
4EKI



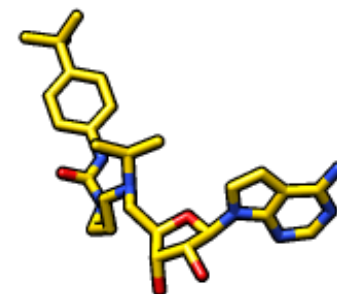
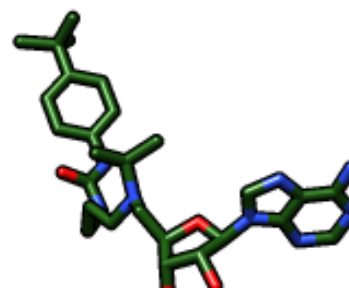
4ER0



4ER5



Experimental Conformation Cross-Docking



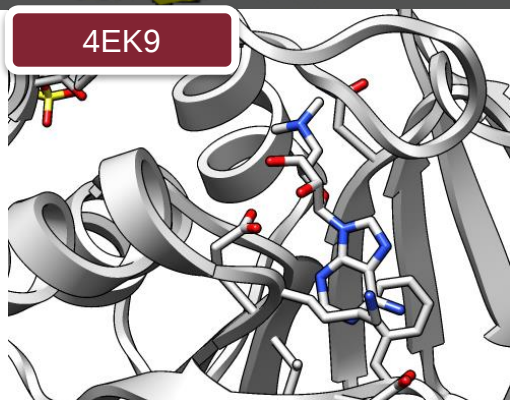
Random Conformation Cross-Docking



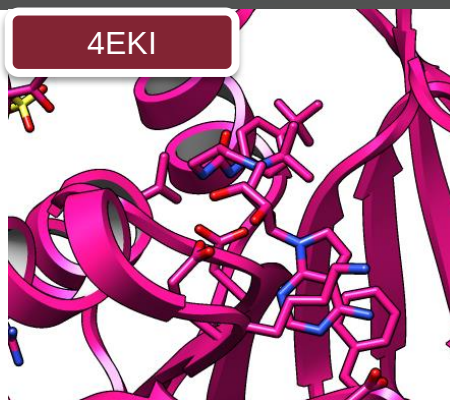
Docking Assessment

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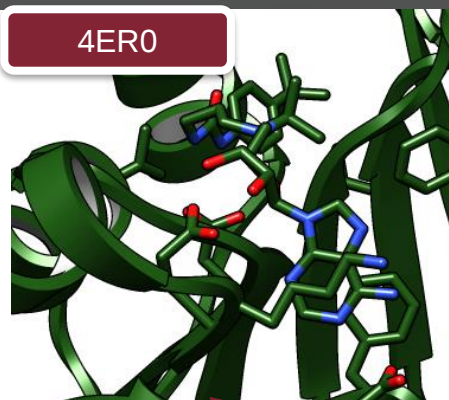
4EK9



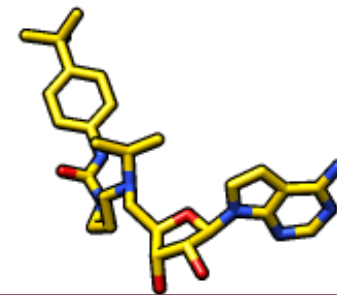
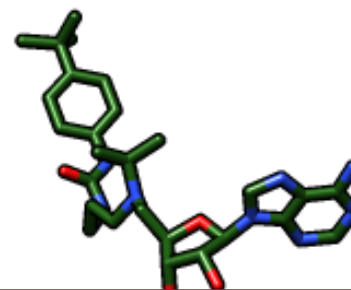
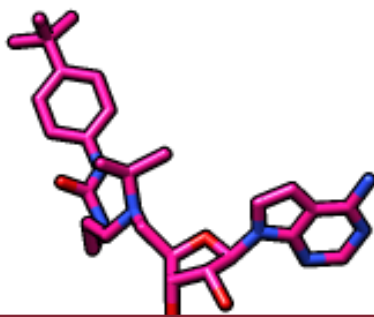
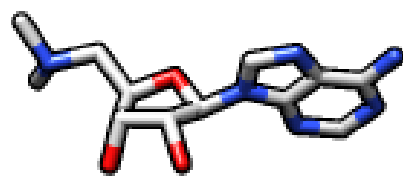
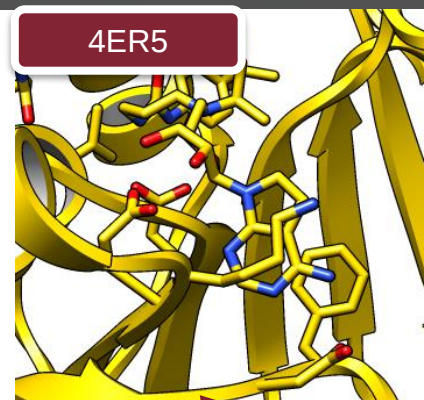
4EKI



4ER0



4ER5



Experimental Conformation Cross-Docking

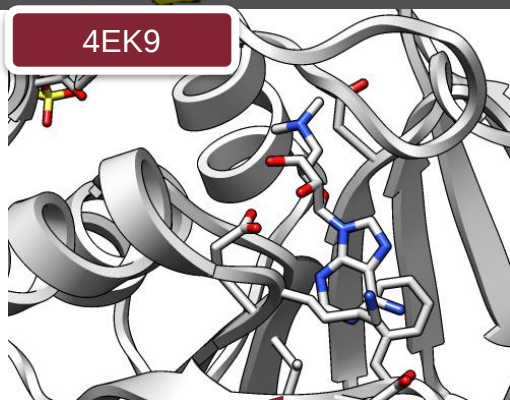
Random Conformation Cross-Docking



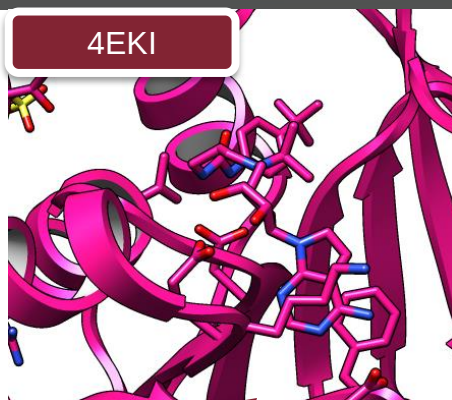
Docking Assessment

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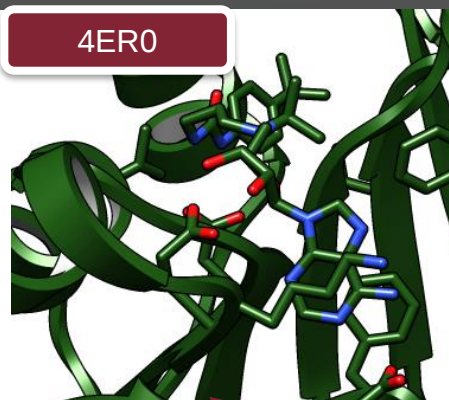
4EK9



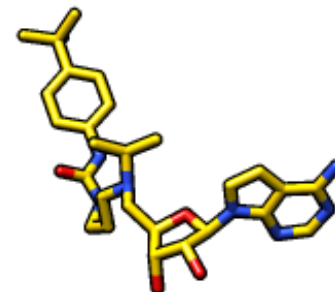
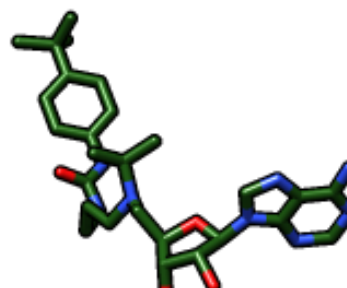
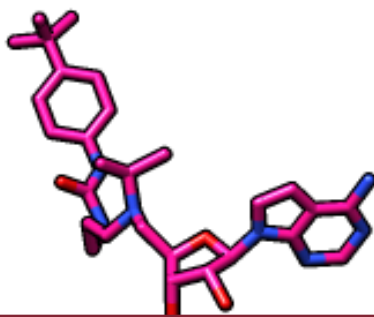
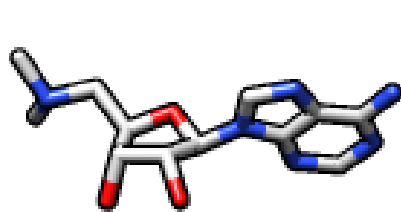
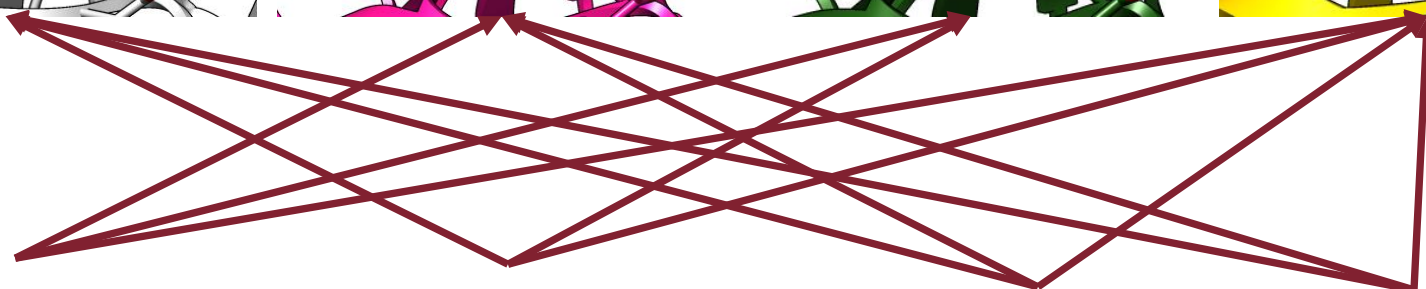
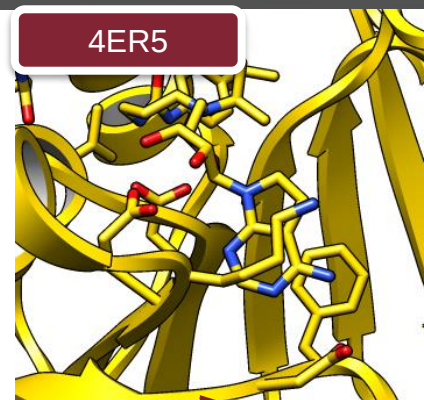
4EKI



4ER0



4ER5



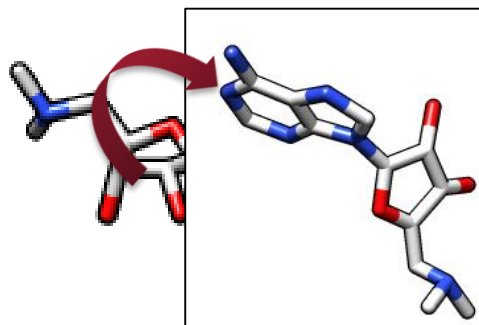
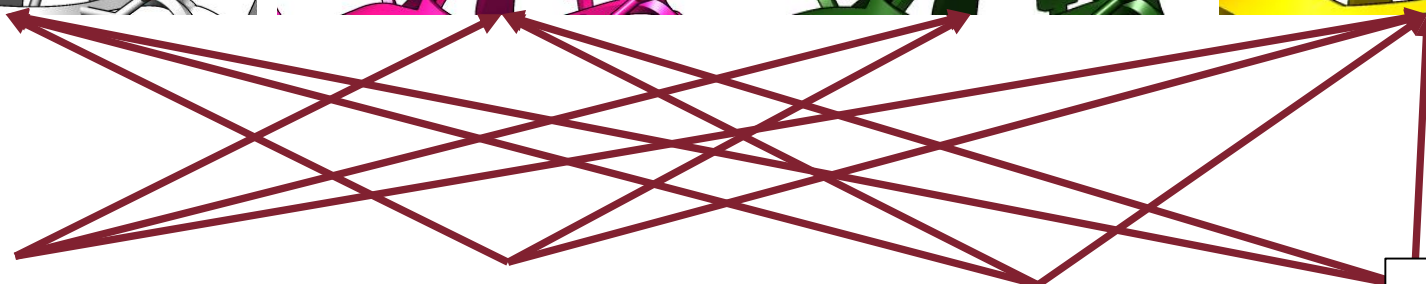
Experimental Conformation Cross-Docking

Random Conformation Cross-Docking

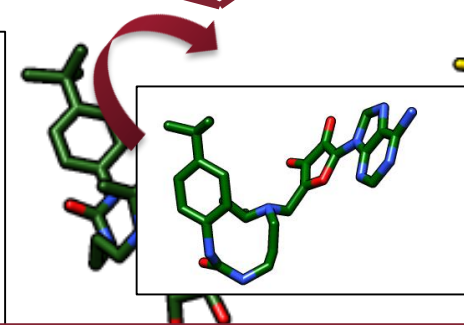
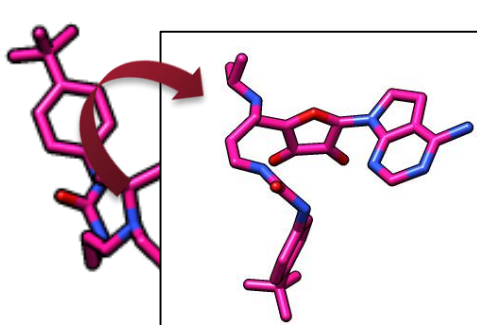


Docking Assessment

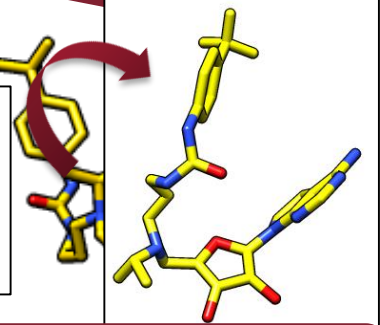
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Experimental Conformation Cross-Docking



Random Conformation Cross-Docking





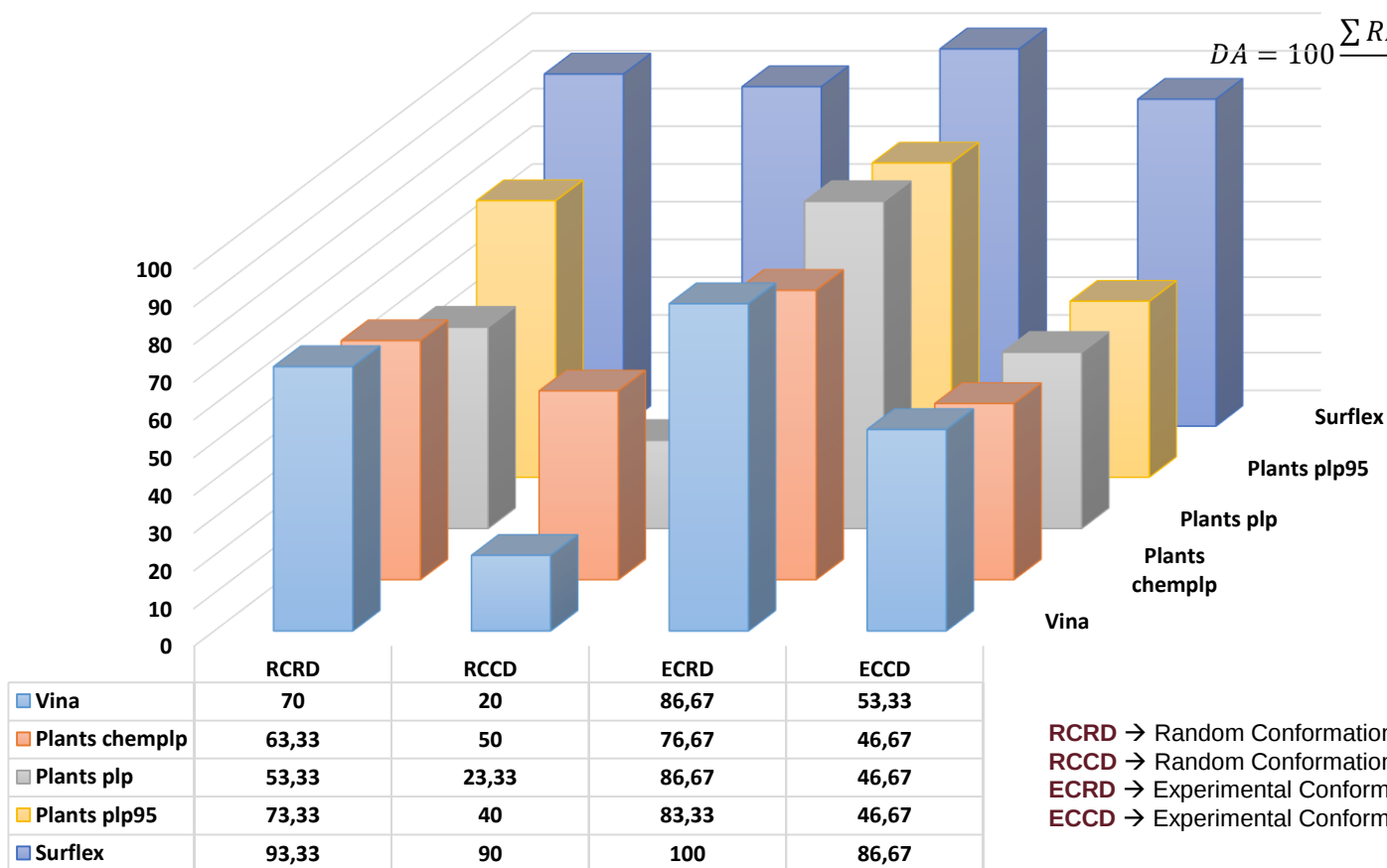
Docking Assessment

by **www.RCMD.it**

Docking Accuracy

$$RMSD = \sqrt{\frac{\sum_{i=1}^N d_i^2}{N}}$$

$$DA = 100 \frac{\sum RMSD_{(0-2)} + \sum RMSD_{(2-3)}}{N}$$





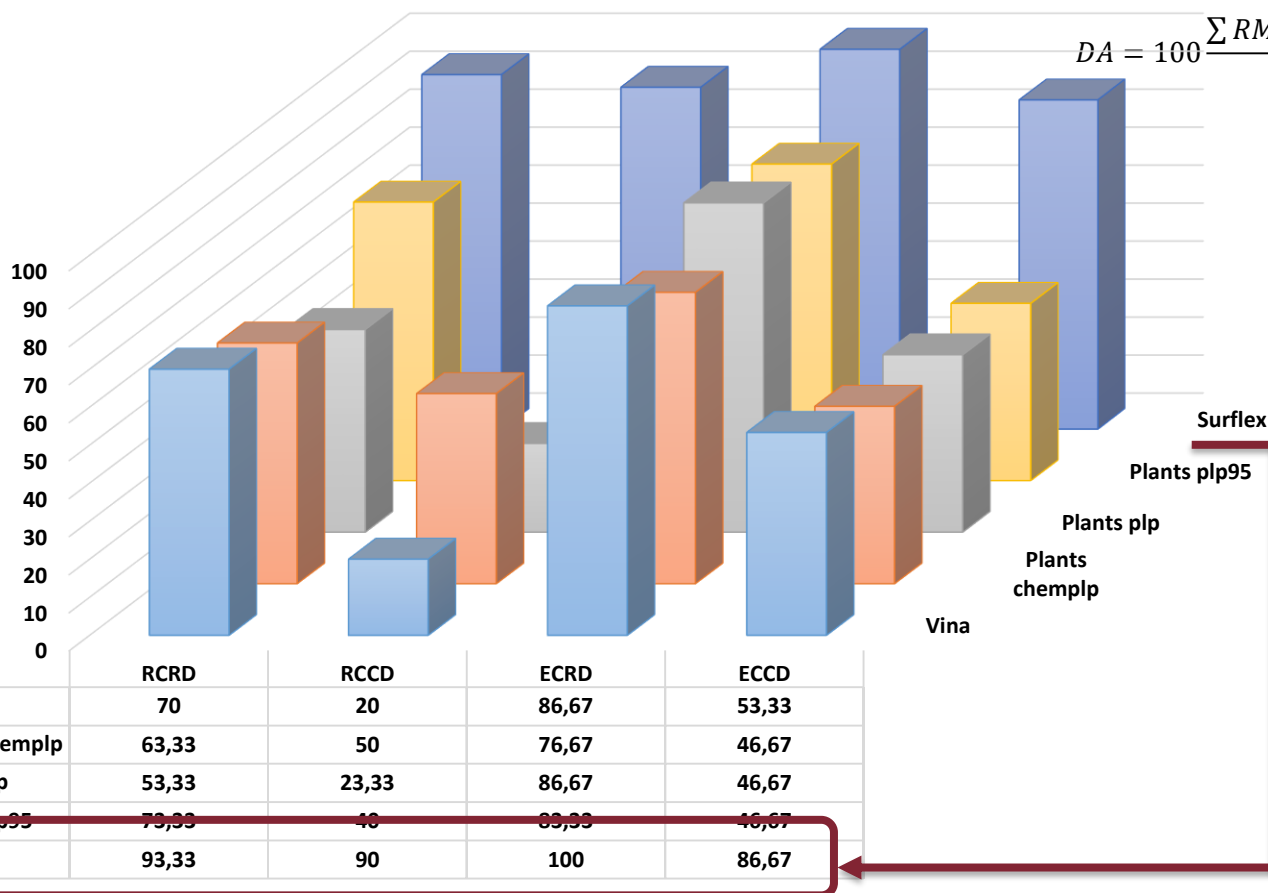
Docking Assessment

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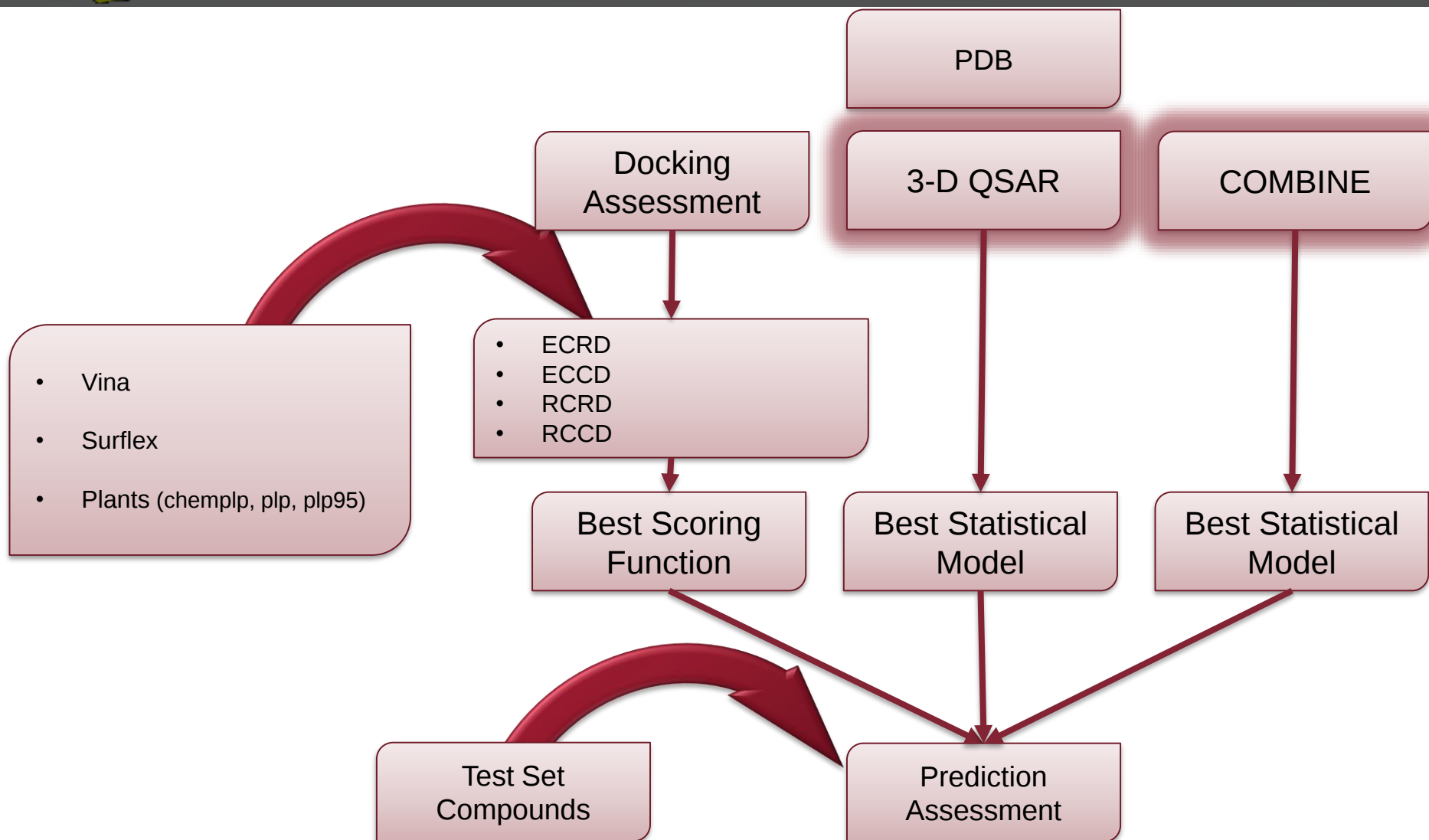
Docking Accuracy

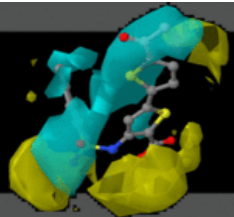
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Workflow





3-D QSAR

by www.RCMD.it

(3-D QSAR)

3-D Quantitative Structure-Activity Relationships

Explanation biological data with three-dimesional approach;

Optimization existing compounds;

Prediction of new compounds not tested or synthesized yet;

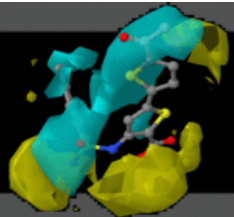
Training
Set
Selection

Molecular
Alignment

Molecular
Interaction
Field (MIF)
Calculation

Statistical
Model

Internal,
External
Validations



3-D QSAR

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(3-D QSAR)

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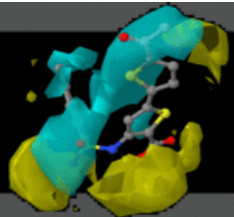
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by www.RCMD.it

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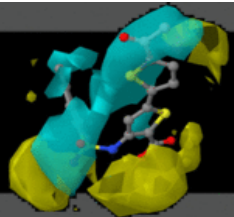
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3-D QSAR

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(3-D QSAR)

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$$Y = \beta_0 + \beta_1 x_1 + \beta_a x_a + \dots + \beta_n x_n$$



3-D QSAR

by www.rcmd.it

(3-D QSAR)

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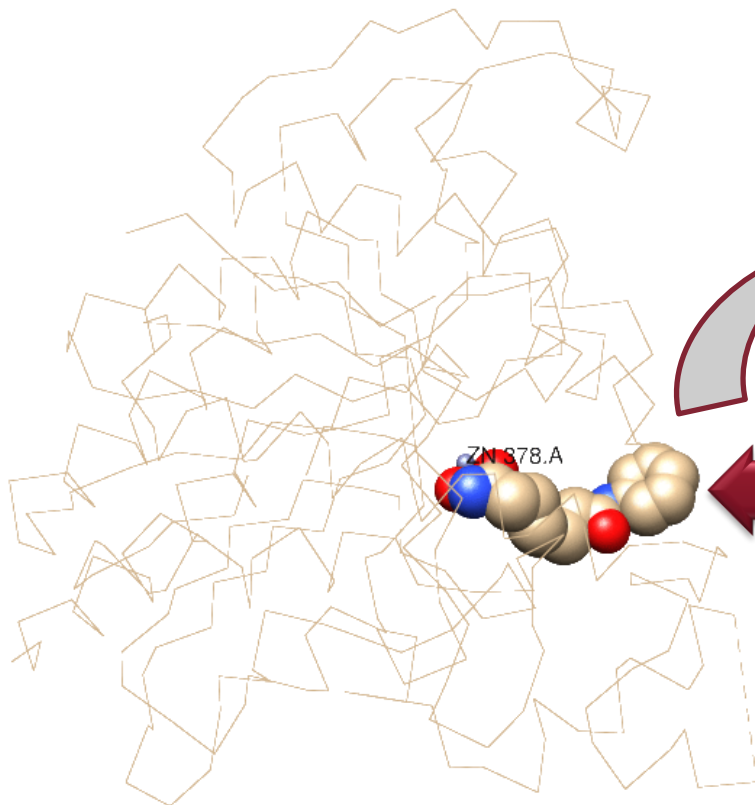
Molecular
Interaction
Field (MIF)
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Statistical
Model

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External
Validations

$$q^2 = 1 - \frac{\sum (y_{exp} - y_{pred})^2}{\sum y_{exp} - \bar{y})^2}$$

$$SDEP = \sqrt{\sum \frac{(y_{exp} - y_{pred})^2}{n - 1}}$$



$$\Delta U = \sum_{i=1}^{n_l} \sum_{j=1}^{n_r} u_{ij}^{\text{VDW}} + \sum_{i=1}^{n_l} \sum_{j=1}^{n_r} u_{ij}^{\text{ELE}}$$

Journal of
Medicinal Chemistry

Subscriber access provided by UNIVERSITA DI ROMA LA SAPIENZA

Prediction of Drug Binding Affinities by Comparative Binding Energy Analysis

Angel R. Ortiz, M. Teresa Pisabarro, Federico Gago, and Rebecca C. Wade

J. Med. Chem., 1995, 38 (14), 2681-2691 • DOI: 10.1021/jm00014a020 • Publication Date (Web): 01 May 2002

The diagram illustrates the PLS regression model structure. It shows a matrix of predictor variables (X) and a vector of response variables (Y). The X matrix has rows labeled Cplx 1, Cplx 2, Cplx 3, ..., Cplx m and columns labeled Res1, Res2, Res3, ..., Res-n. The Y vector has elements Y1, Y2, Y3, ..., Ym. A double-headed arrow labeled 'PLS' connects the X matrix and the Y vector.

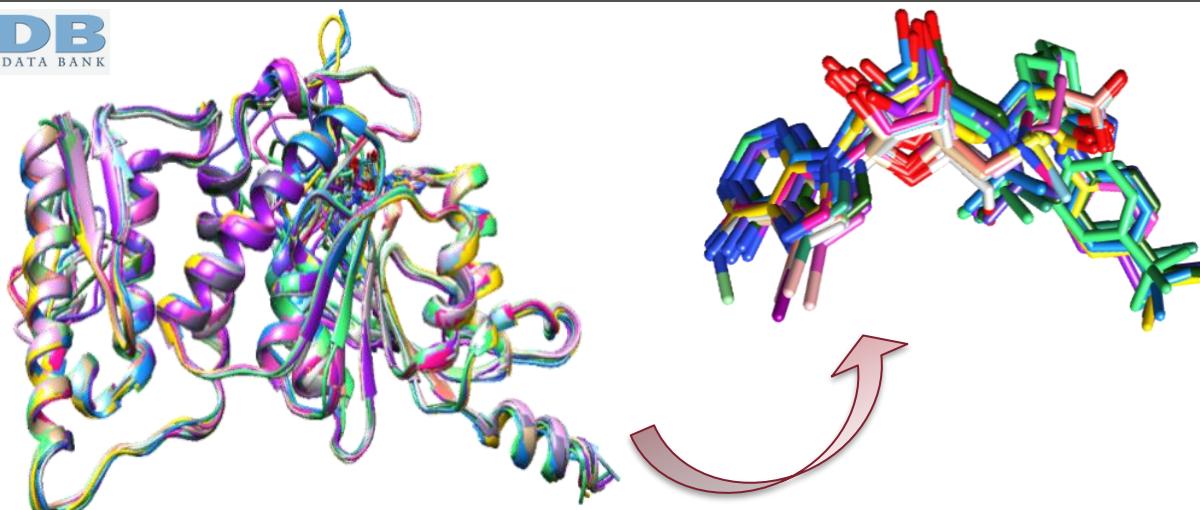
COMBINE Model



3-D QSAR

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RCSB PDB
PROTEIN DATA BANK



Model	Probe	r^2	q^2_{L50}	$SDEP_{L50}$	PC	GRID	Cut Off	Zeroing	Min STD
1	A	0.83	0.70	0.994	1	2.45	4	0.008	0.005
2	B	0.83	0.70	0.995	1	2.45	4	0.010	0.005
3	D	0.96	0.70	0.992	3	2.10	5	0.002	0.050
4	OA	0.97	0.79	0.837	3	2.30	4	0.003	0.015
5	N	0.97	0.79	0.834	3	2.30	5	0.002	0.015
6	A	0.96	0.78	0.836	3	2.30	5	0.002	0.015
7	B	0.84	0.60	1.145	2	2.10	3	0.005	0.050
8	d	0.85	0.79	0.822	1	1.95	1	0.001	0.015

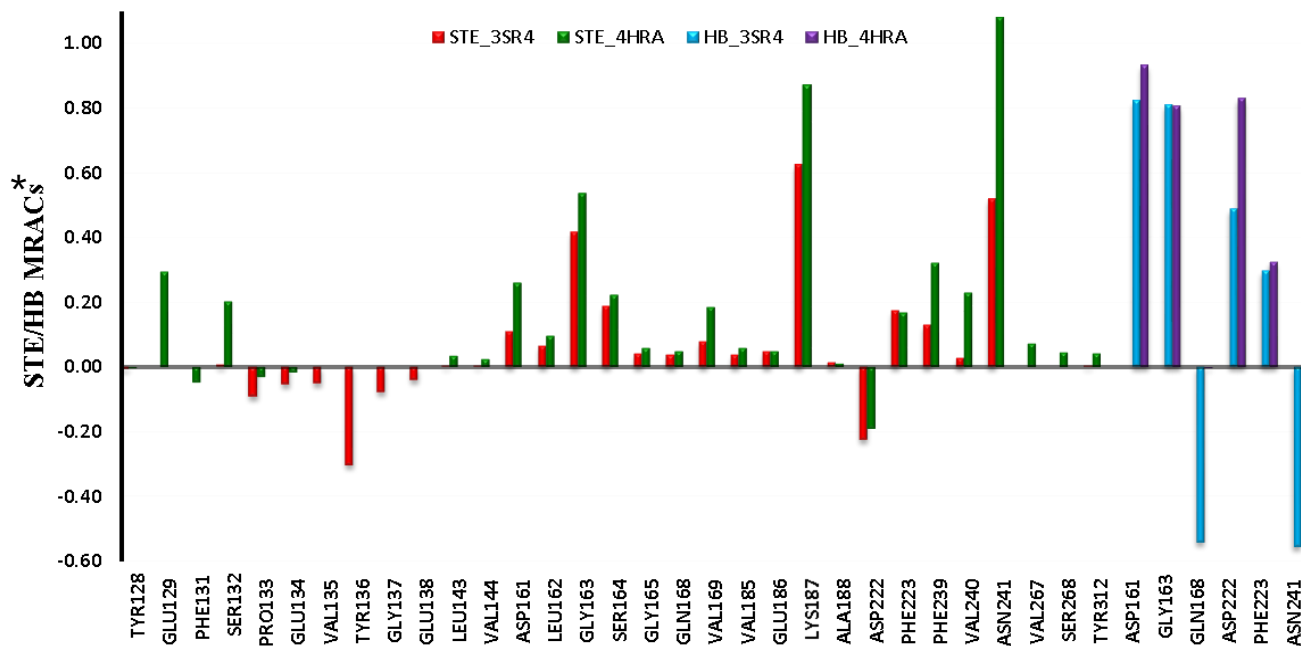
OA Hydrogen binding acceptor oxygen
N Amidic nitrogen



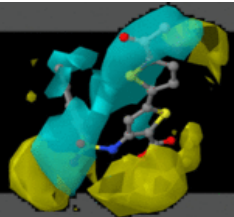
COMBINE

by www.RCMD.it

#	Molecule-Residue Interaction Field Combination	PC	Fitting		LOO		L50		LHO	
			r^2	SDEC	q^2	SDEP	q^2	SDEP	q^2	SDEP
7s	STE.HB	4	0.96	0.36	0.80	0.81	0.78	0.85	0.69	1.01



*STE/HB molecule-residue activity contribution



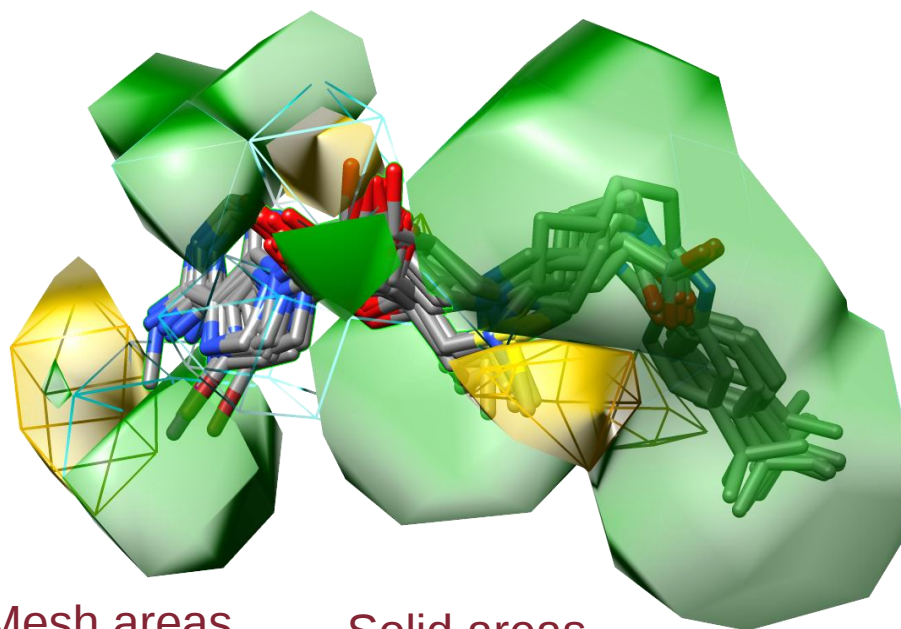
Countourn Maps

by www.RCMD.it

Average activity contribution plot

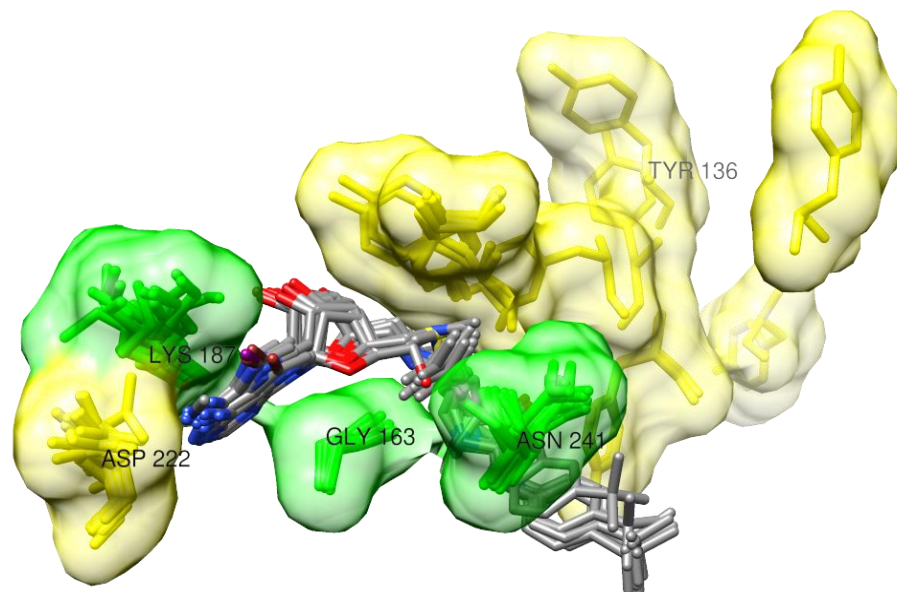
3-D QSAR: OA and N probes

COMBINE: STE.HD molecular interaction fields



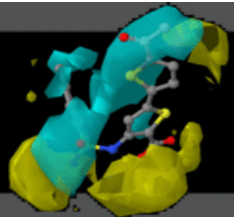
Mesh areas

Solid areas



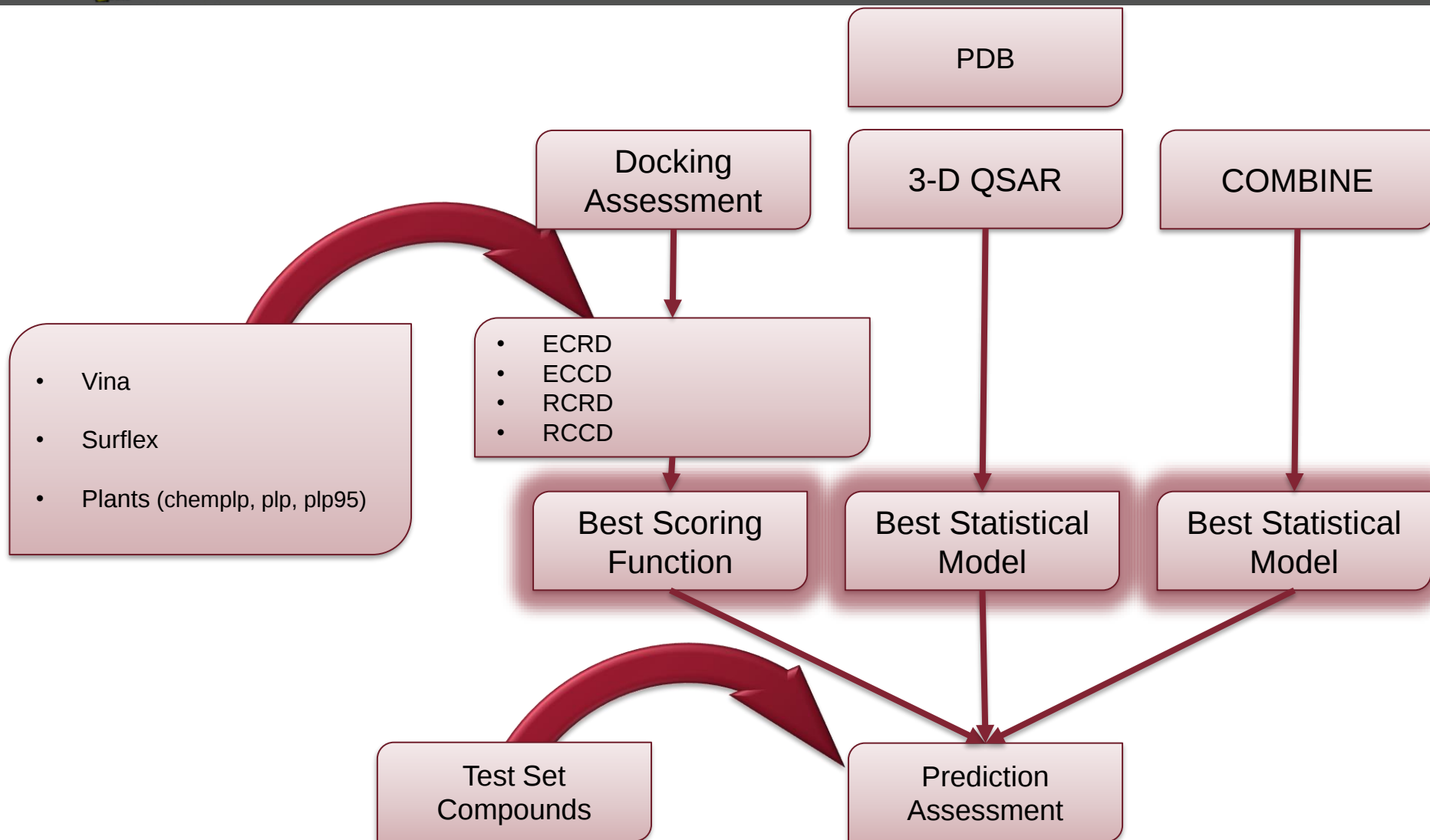
Solid areas





Overflow

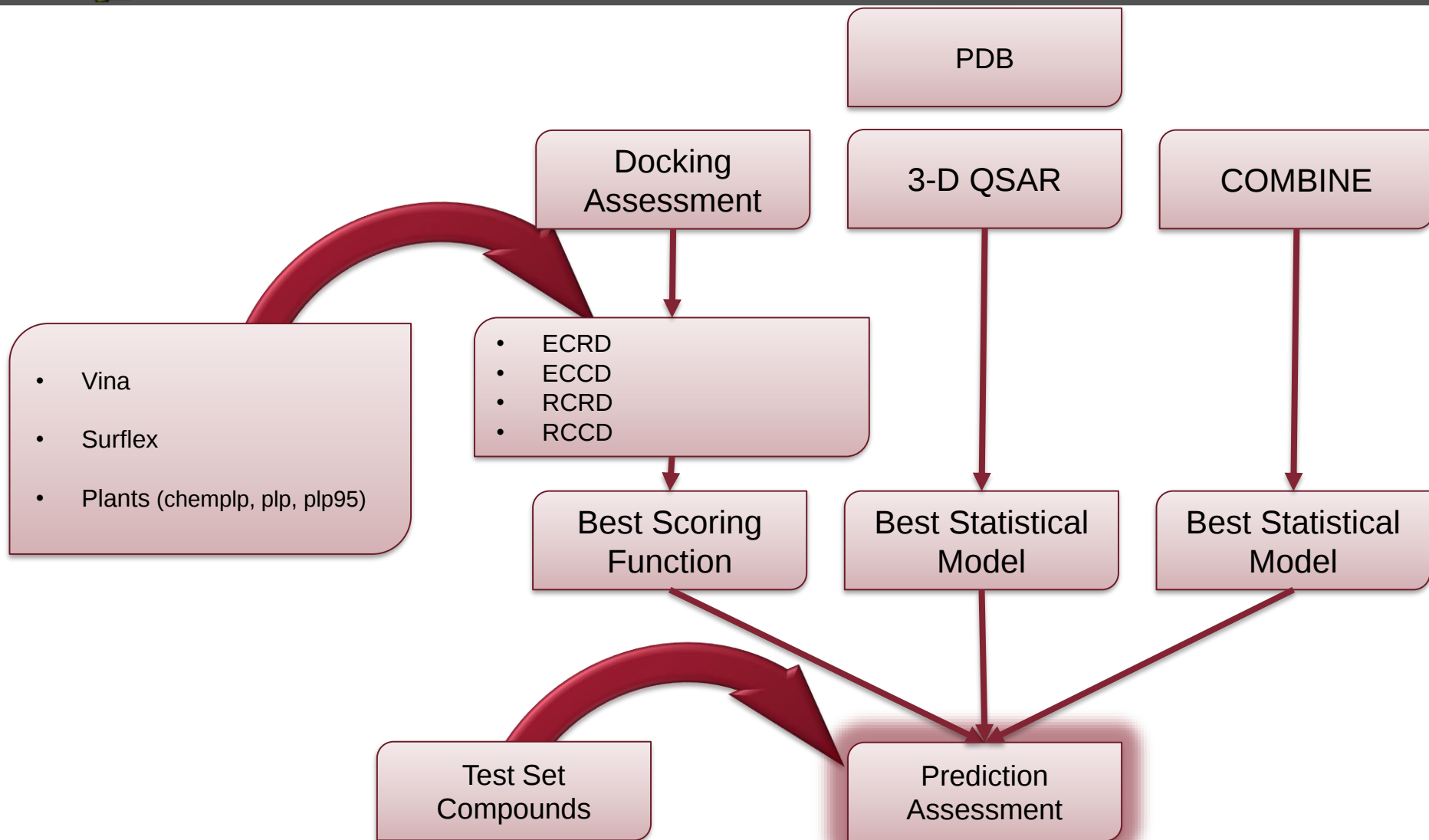
by www.RCMD.it





Overflow

by www.RCMD.it





Modelled External Test Set

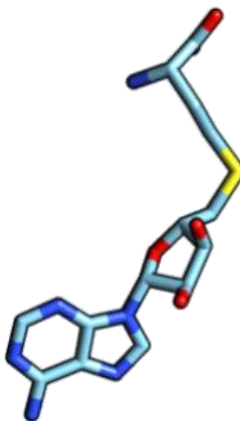
by www.RCMD.it

PDB ID Activity
(pIC₅₀^a o pK_i^b)

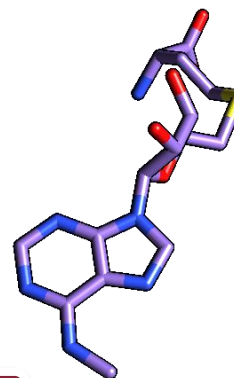
1TS	4.00 ^b
2TS	4.34 ^b
3TS	4.66 ^b
4TS	4.66 ^b
5TS	4.70 ^b
6TS	4.74 ^b
7TS	4.80 ^a
8TS	4.80 ^b
9TS	4.92 ^b
10TS	5.72 ^b
11TS	5.96 ^b
12TS	5.96 ^b
13TS	6.07 ^b
14TS	6.92 ^a
15TS	6.26 ^b
16TS	6.96 ^a
17TS	7.09 ^b
18TS	7.15 ^b
19TS	7.24 ^b
20TS	7.42 ^a
21TS	8.40 ^b
22TS	8.89 ^b
23TS	8.96 ^b
24TS	9.10 ^b

- Vin
- Sur
- Pla

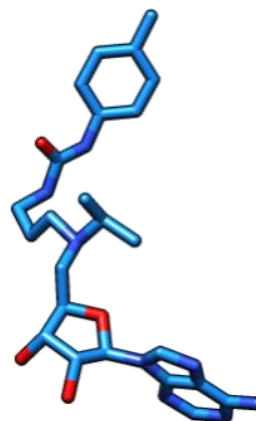
3QOX



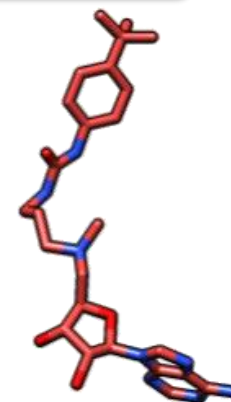
3SR4



4EQZ



4EKG

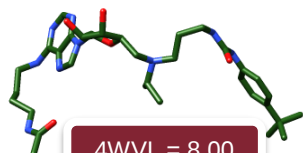




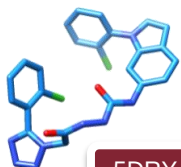
Cristallized External Test Set

by www.rcmd.it

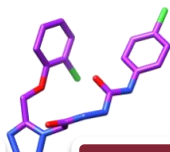
Crystallized External Test Set



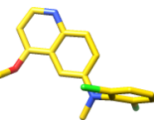
4WVL = 8.00



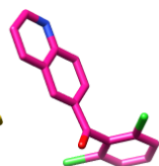
5DRY = 4.70



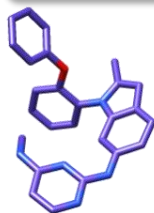
5DRT = 5.36



5DTR = 4.41



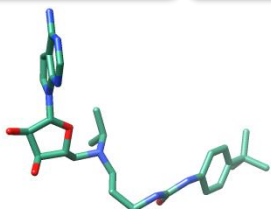
5DTQ = 3.86



5DT2 = 6.82



5DSX = 8.00



4ER3 = 9.53

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Structure-Guided DOT1L Probe Optimization by Label-Free Ligand Displacement

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Letter

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Optimization of a Fragment-Based Screening Hit toward Potent DOT1L Inhibitors Interacting in an Induced Binding Pocket

ACS
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Chemistry Letters

Letter

pubs.acs.org/acsmedchemlett

Discovery of Novel Dot1L Inhibitors through a Structure-Based Fragmentation Approach

Chao Chen,[†] Hugh Zhu,[†] Frédéric Stauffer,[‡] Giorgio Caravatti,[‡] Susanne Vollmer,[‡] Rainer Machauer,[‡] Philipp Holzer,[‡] Henrik Möbitz,[‡] Clemens Scheufler,[‡] Martin Klumpp,[‡] Ralph Tiedt,[‡] Kim S. Beyer,[‡] Keith Calkins,[‡] Daniel Guthy,[‡] Michael Kiffe,[‡] Jeff Zhang,[†] and Christoph Gaul^{*,‡}

[‡]Novartis Institutes for Biomedical Research, 4002 Basel, Switzerland

[†]Novartis Institutes for Biomedical Research, Shanghai 201203, China



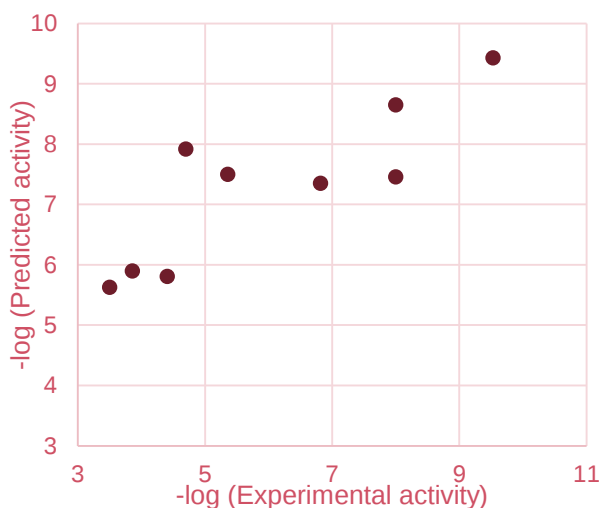
Statistical Results

by www.RCMD.it

Model	Probe	r^2	q^2_{L50}	SDEP _{L50}	PC	GRID	Cut Off	Zeroing	Min STD
1	A	0.83	0.70	0.994	1	2.45	4	0.008	0.005
2	C	0.83	0.70	0.995	1	2.45	4	0.010	0.005
3	HD	0.96	0.70	0.992	3	2.10	5	0.002	0.050
4	OA	0.97	0.79	0.837	3	2.30	4	0.003	0.015
5	N	0.97	0.79	0.834	3	2.30	5	0.002	0.015
6	NA	0.96	0.78	0.836	3	2.30	5	0.002	0.015
7	e	0.84	0.60	1.145	2	2.10	3	0.005	0.050
8	d	0.85	0.79	0.822	1	1.95	1	0.001	0.015

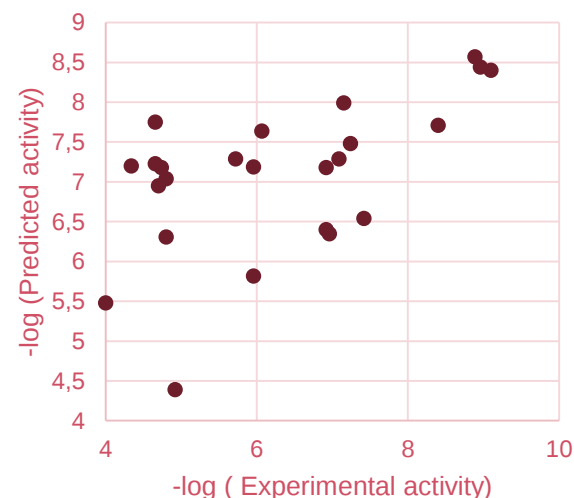
Cristallized External Test Set

Predicted activity OA probe



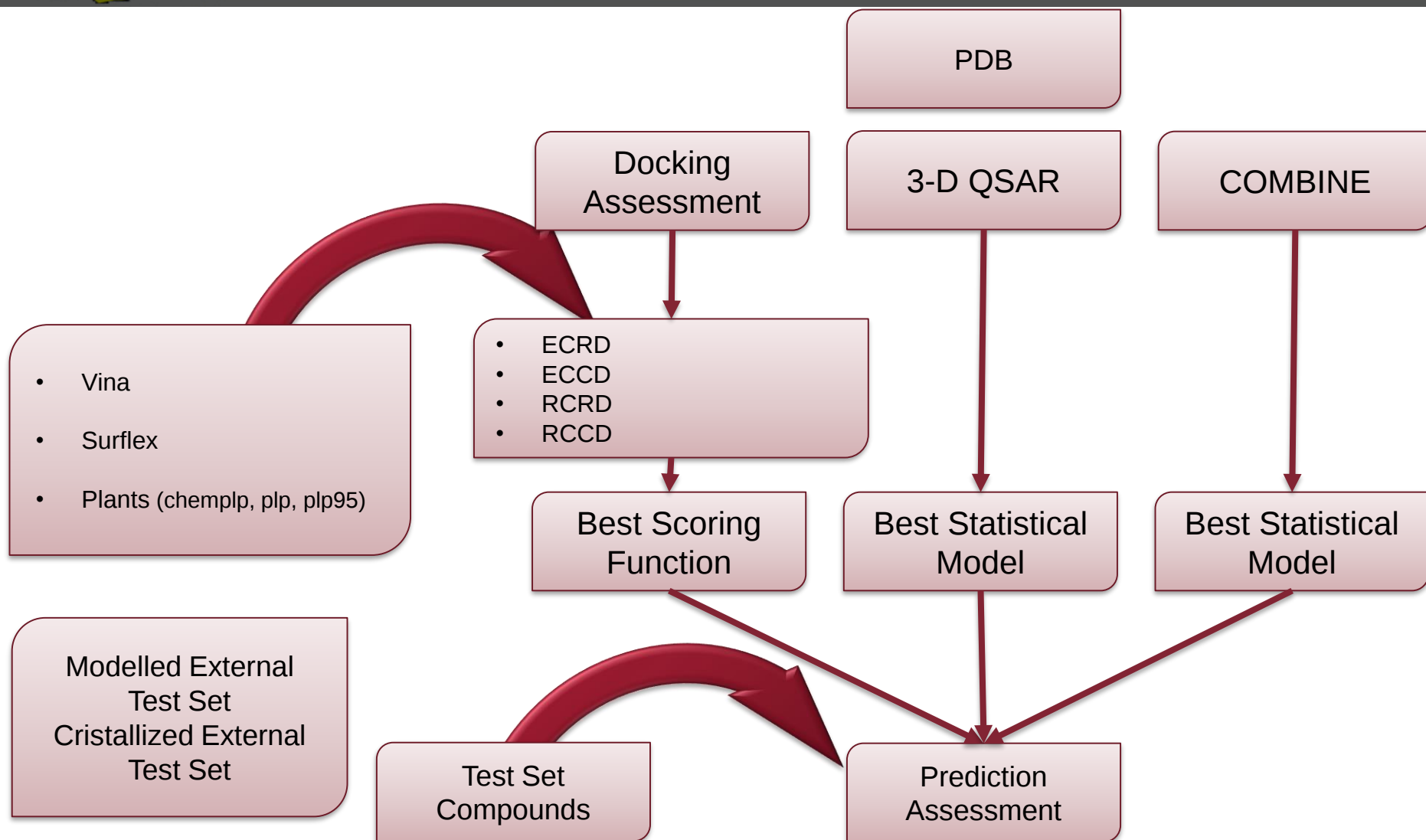
Modelled External Test Set

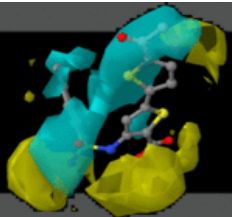
Predicted activity OA probe





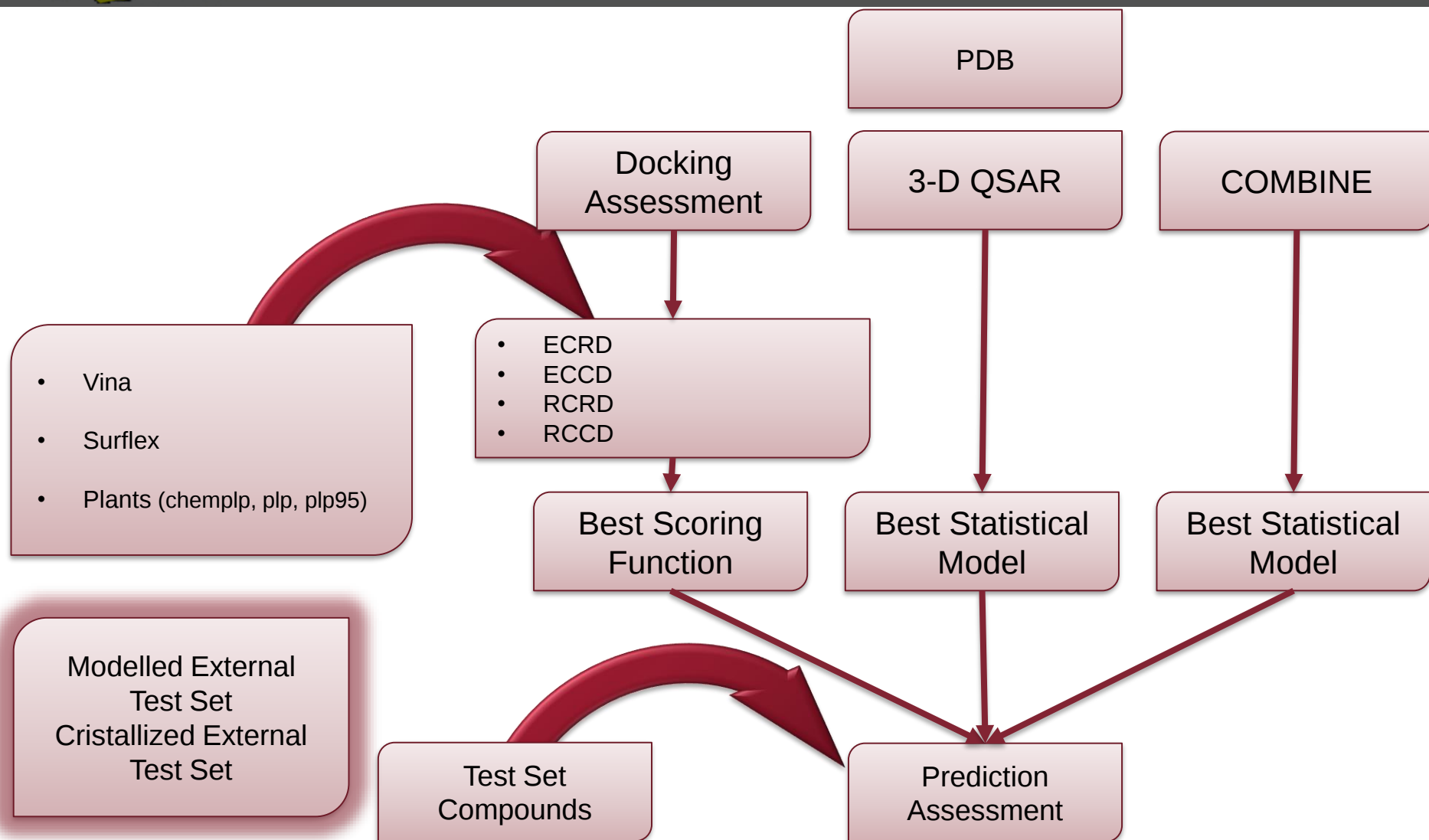
Overflow

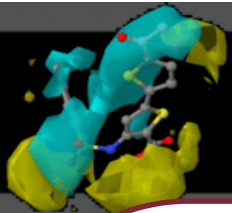




Overflow

by **www.RCMD.it**





Overflow

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Journal of
**Medicinal
Chemistry**

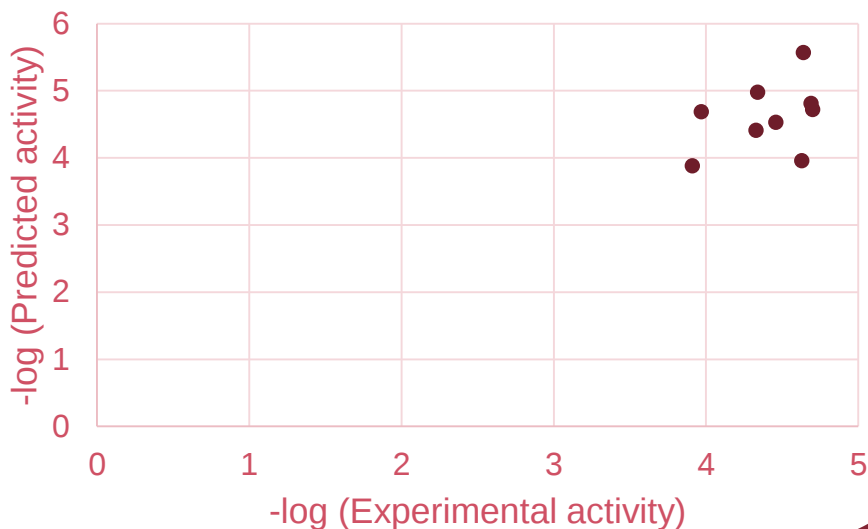
Article

pubs.acs.org/jmc

Discovery of Novel Disruptor of Silencing Telomeric 1-Like (DOT1L) Inhibitors using a Target-Specific Scoring Function for the (S)-Adenosyl-L-methionine (SAM)-Dependent Methyltransferase Family

Yulan Wang,^{#,†,‡,¶} Linjuan Li,^{#,§,¶} Bidong Zhang,^{#,‡} Jing Xing,^{#,‡} Shijie Chen,^{#,‡} Wei Wan,^{#,‡}
Yakai Song,^{#,¶} Hao Jiang,^{#,‡} Hualiang Jiang,^{#,‡,§} Cheng Luo,^{*,#,‡} and Mingyue Zheng^{*,#,‡,¶}

Prediction Set





Overflow

by www.RCMD.it

87 compounds

Prof Mai's Lab

PREDICTION SET

Validated

Docking

3-D QSAR

COMBINE

Best Scoring
Function:Surflex

Best Statistical
Model:OA, N

Best Statistical
Model:STE.HB

#	Probe OA	Probe N	COMBINE	Average	pIC ₅₀
<u>1MPS</u>	6.42	6.63	4.66	5.90	5.14
<u>2MPS</u>	6.99	6.99	4.63	6.20	5.10

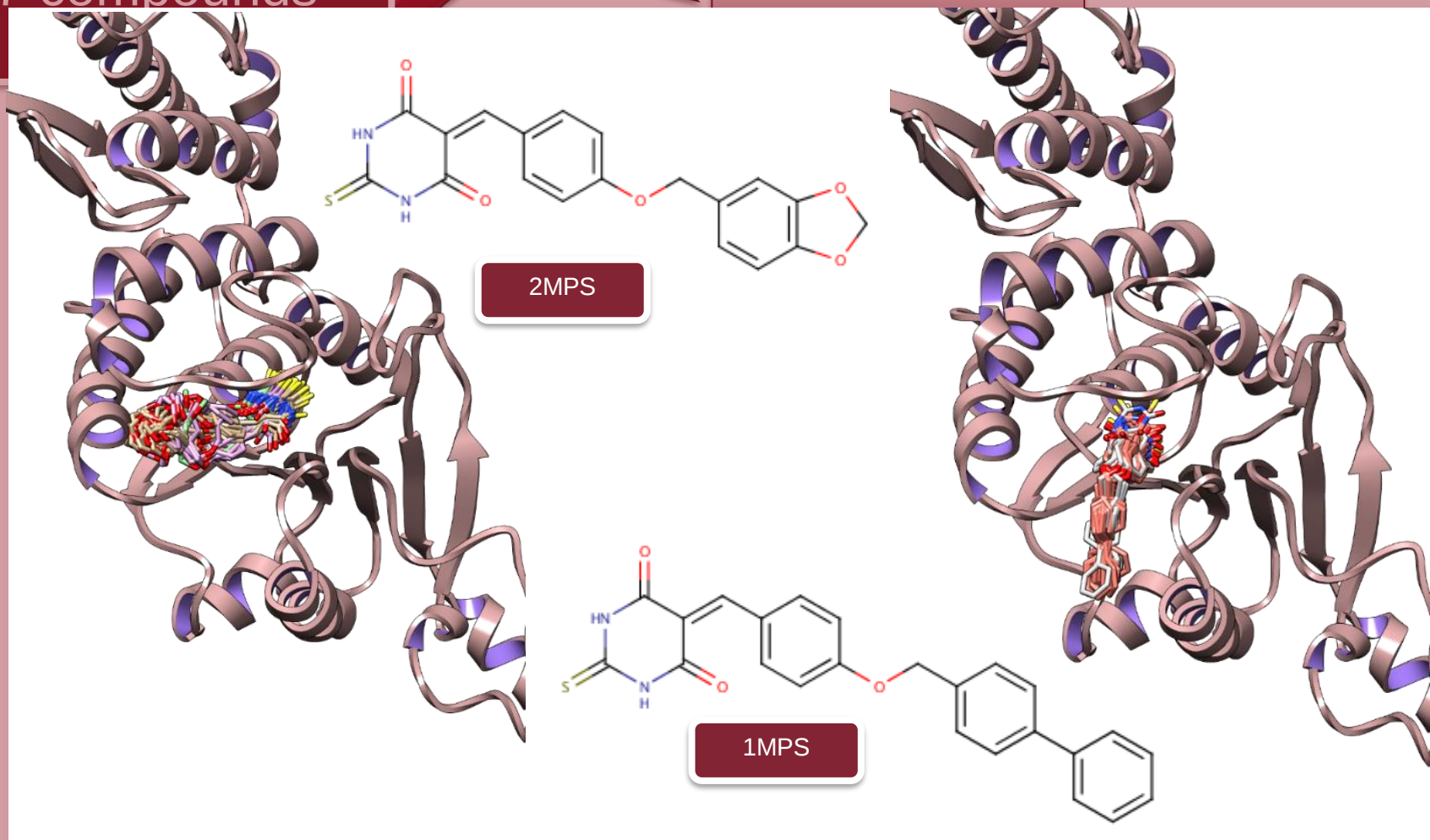


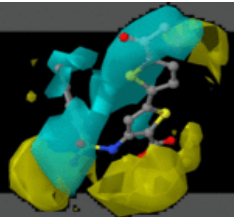
Overflow

by www.RCMD.it

87 compounds

PREDICTION SET





Conclusion

by www.RCMD.it

- Using a Docking assessment was identified a best docking software for DOT1L target;
- 3-D QSAR and COMBINE models with high robustness were built for DOT1L target;
- Using Docking, 3-D QSAR and COBINE protocol a very comprehensive SB and LB study was developed;
- Using a presented protocol was identified a new chemical scaffold as starting point to synthesize new promising compounds;
- This protocol was accepted on Journal of Computer Aided Molecular Design (JCAM) *(Sabatino, M.; Rotili, D., Patsilnakos A.; Forgione, M.; Tomaselli, D.; Alby, F.; Arimondo, P.; Mai, A.; Ragno, R., Disruptor of Telomeric Silencing 1-Like (DOT1L): Disclosing a New Class of Non-nucleoside Inhibitors by Means of Ligand-Based and Structure-Based Approaches.)*



Essenziali Oils

by www.RCMD.it



Essential Oils are organic complex mixtures extracted from *aromatic* plants thanks physical process.

High percentage of:

Terpenes

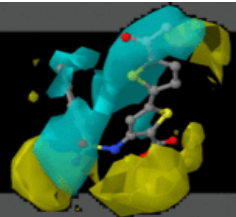
Oxygenated compounds

To extract the essential oils are available several techniques:

Ultrasound

Steam distillation, Hydro-distillation

Solvent extraction, Supercritical fluids extraction



Essenziali Oils

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Essential Oils are organic complex mixtures extracted from *aromatic* plants thanks physical process.

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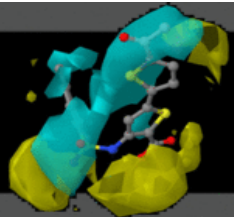
Oxygenated compounds

To extract the essential oils are available several techniques:

Ultrasound

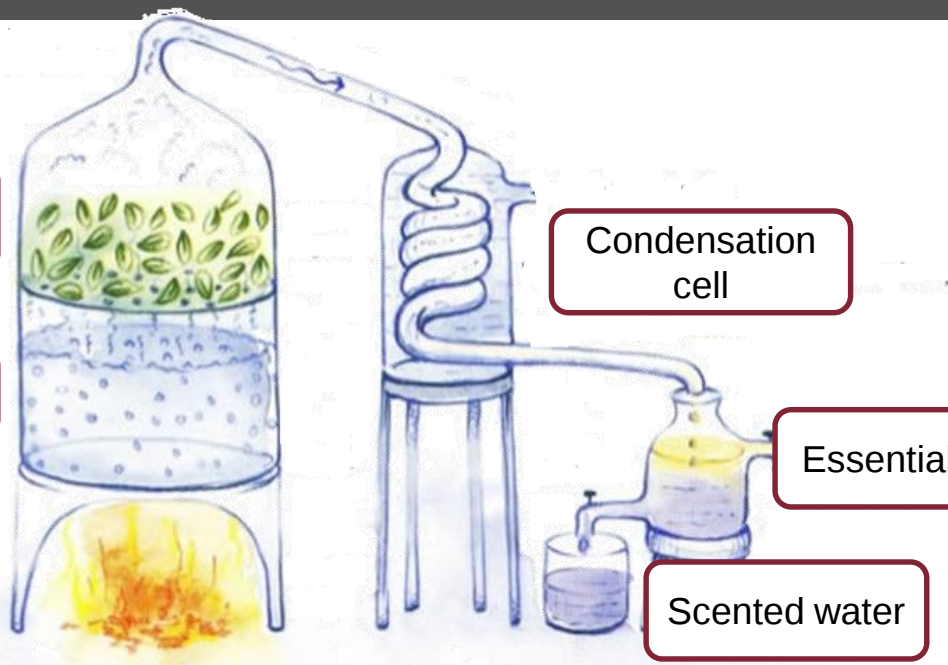
Steam distillation, Hydro-distillation

Solvent extraction, Supercritical fluids extraction



Steam distillation

by www.RCMD.it

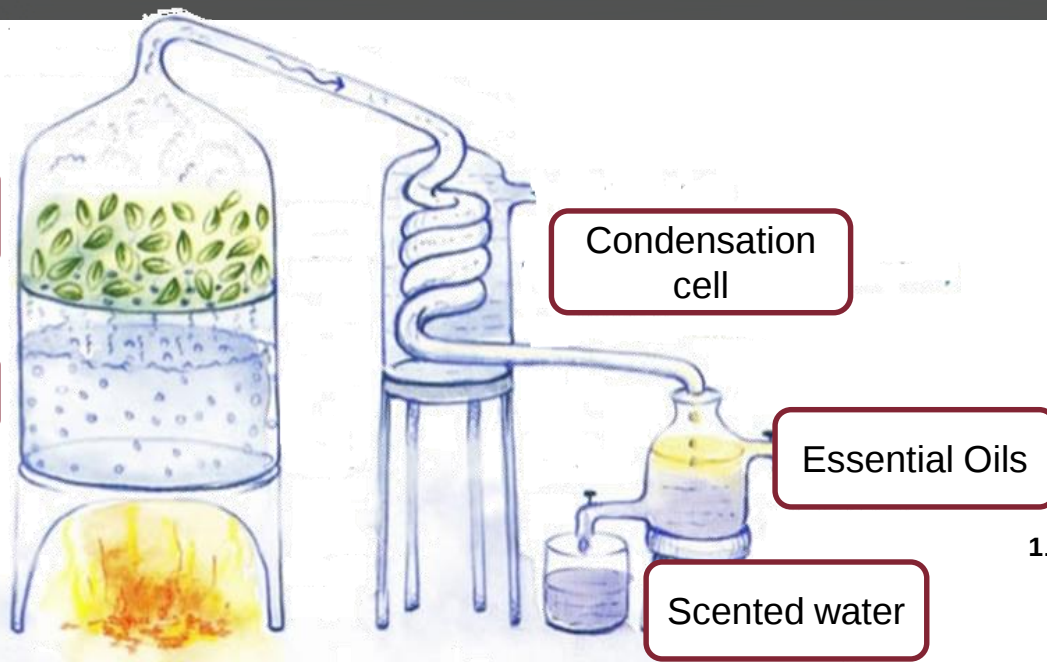


1. *Calamintha nepeta* L.; 2. *Ridolfia segetum* Mor.;
3. *Sideritis purpurea* Tal. Ex Ben.; 4. *Melissa altissima* Sm.; 5. *Mentha suaveolens*



Steam distillation

by www.RCMD.it



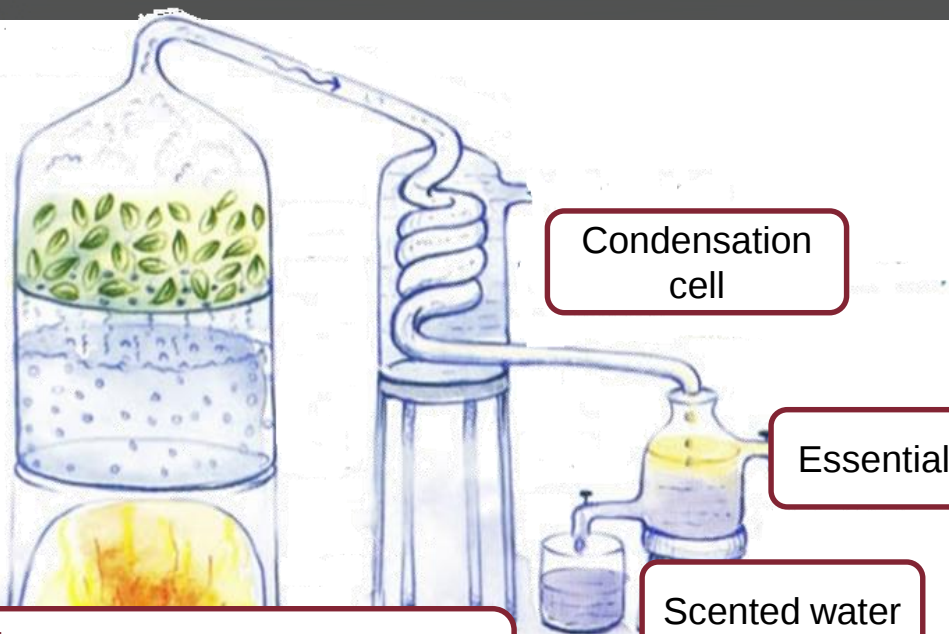
1. *Calamintha nepeta* L.;
2. *Ridolfia segetum* Mor.;
3. *Sideritis purpurea* Tal. Ex Ben.;
4. *Melissa altissima* Sm.;
5. *Mentha suaveolens*

Month	Sampling temp	Kind of plants
June	1h	Fresh
July	2h	Dry
August	3h	
September	6h	
October	12h	
	24h	



Steam distillation

by www.RCMD.it



Aromatic Plants

Water

Condensation cell

Essential Oils

Scented water



1. *Calamintha nepeta* L.;
2. *Ridolfia segetum* Mor.;
3. *Sideritis purpurea* Tal. Ex Ben.;
4. *Melissa altissima* Sm.;
5. *Mentha suaveolens*

-GC/MS analysis;
(Prof.ssa Garzoli, Prof. Pepi- Roma)

-Anticandidal;
(Prof. Mafredini - Ferrara)

-Antibacterial;
(Prof.ssa Oliva - Roma)

-Antibiofilm;
(Prof.ssa Selan - Roma)

-Antiviral;
(Prof.ssa Palamara - Roma)

Month

June
July
August
September
October

Sampling temp

1h
2h
3h
6h
12h
24h

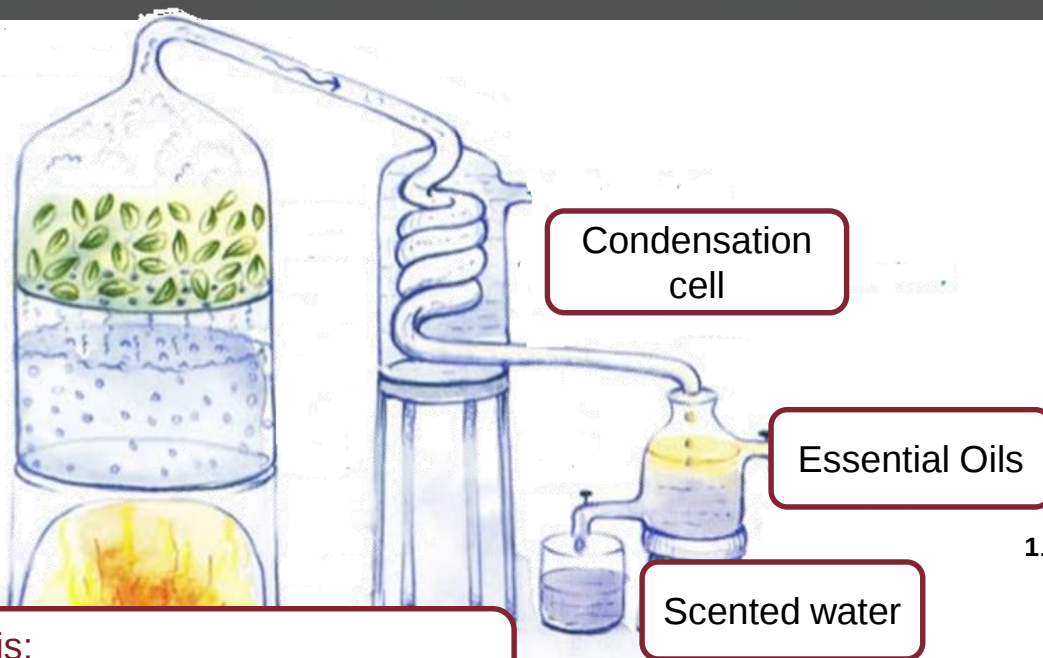
Kind of plants

Fresh
Dry



Steam distillation

by www.RCMD.it



1. *Calamintha nepeta* L.; 2. *Ridolfia segetum* Mor.;
3. *Sideritis purpurea* Tal. Ex Ben.; 4. *Melissa altissima* Sm.; 5. *Mentha suaveolens*

-GC/MS analysis;
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-Antiviral;
(Prof.ssa Palamara - Roma)

Month

June
July
August
September
October

Sampling temp

1h
2h
3h
6h
12h
24h

Kind of plants

Fresh
Dry



Starting Data

by www.RCMD.it

From the 90 Essential oils extracted from three different plants with the explained protocol, were chosen 37 for the Antiviral tests.



Calamintha Nepeta

- July
 - 1 e 2 hours
 - Mix 2 e 5
- August
 - 1, 2, 3 e 6 hours
 - Mix 1,3 e 5
- September
 - 1,2,3 e 6 hours
 - Mix 1,3 e 5
- October
 - 1, 2 e 6 hours
 - Mix 1,3 e 5



Foeniculum Vulgare

- Augsut
 - 2 e 6 hours
- September
 - 1, 2 e 6 hours
- October
 - 1, 3, 6 e 24 hours
 - Mix 3



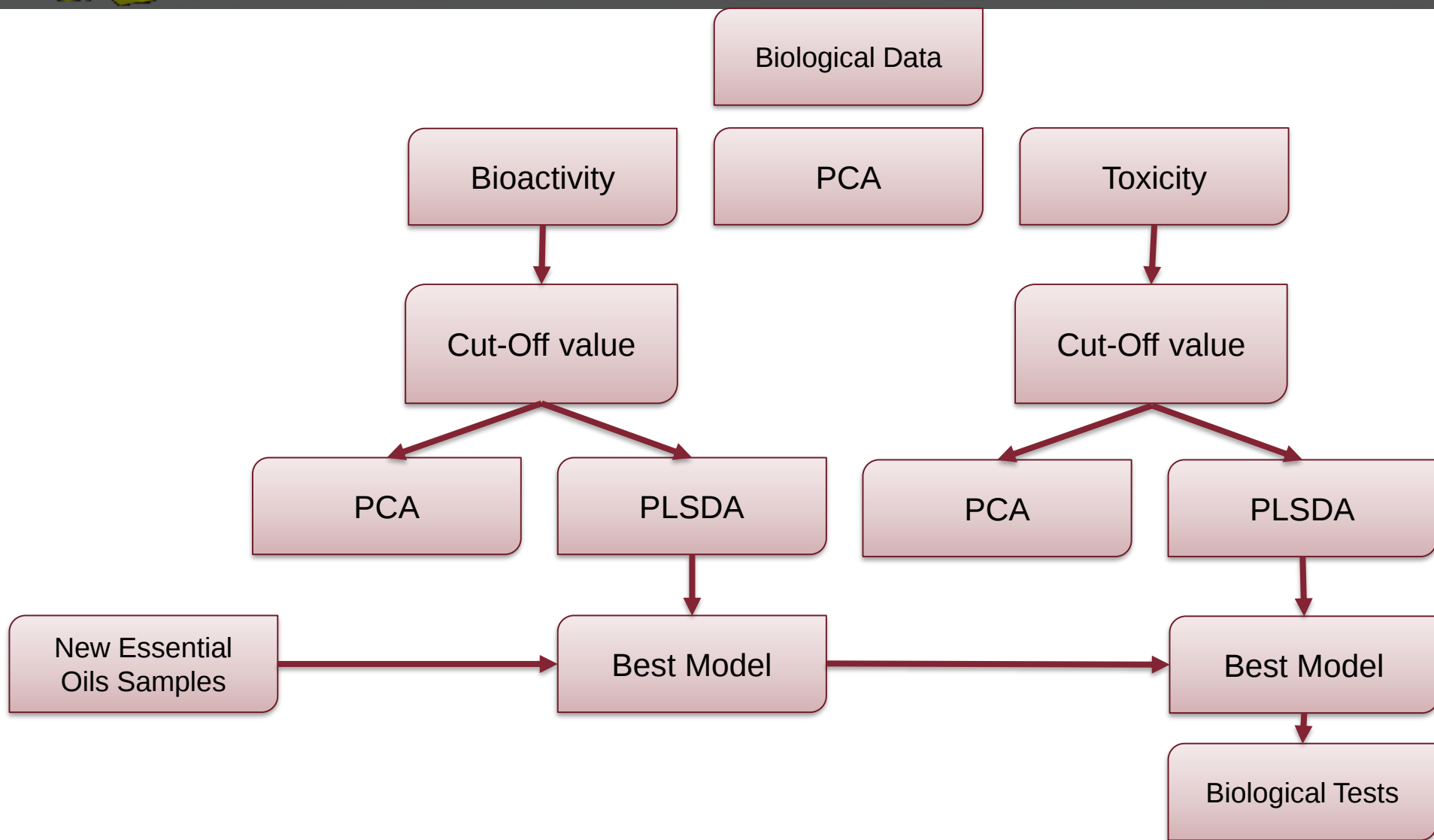
Ridolfia segetum

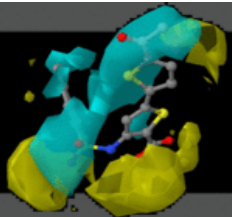
- July 6 e 24 hours
- Mix 4 e 6



Workflow

by www.RCMD.it

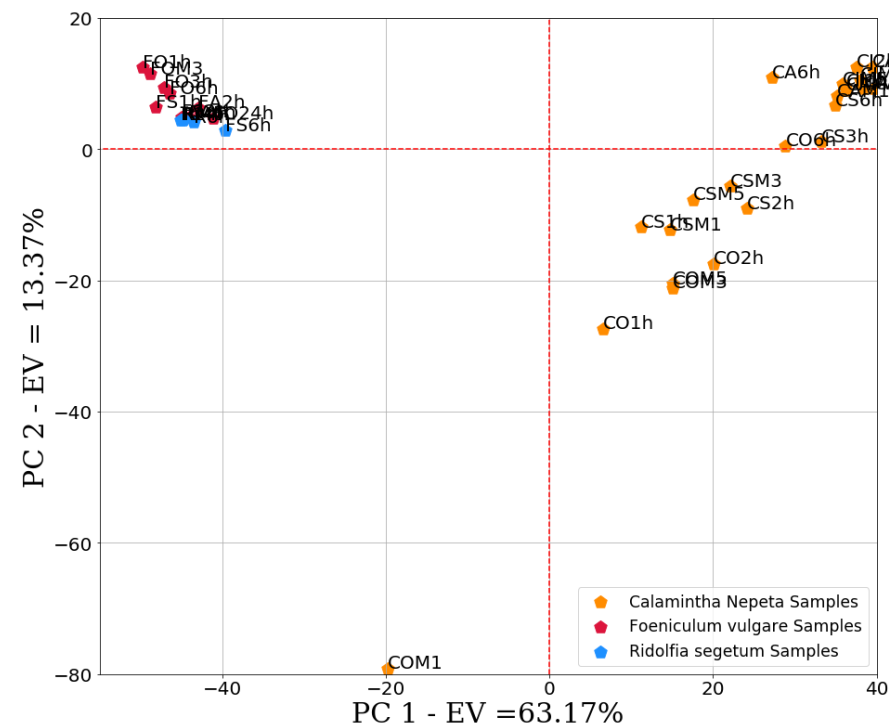




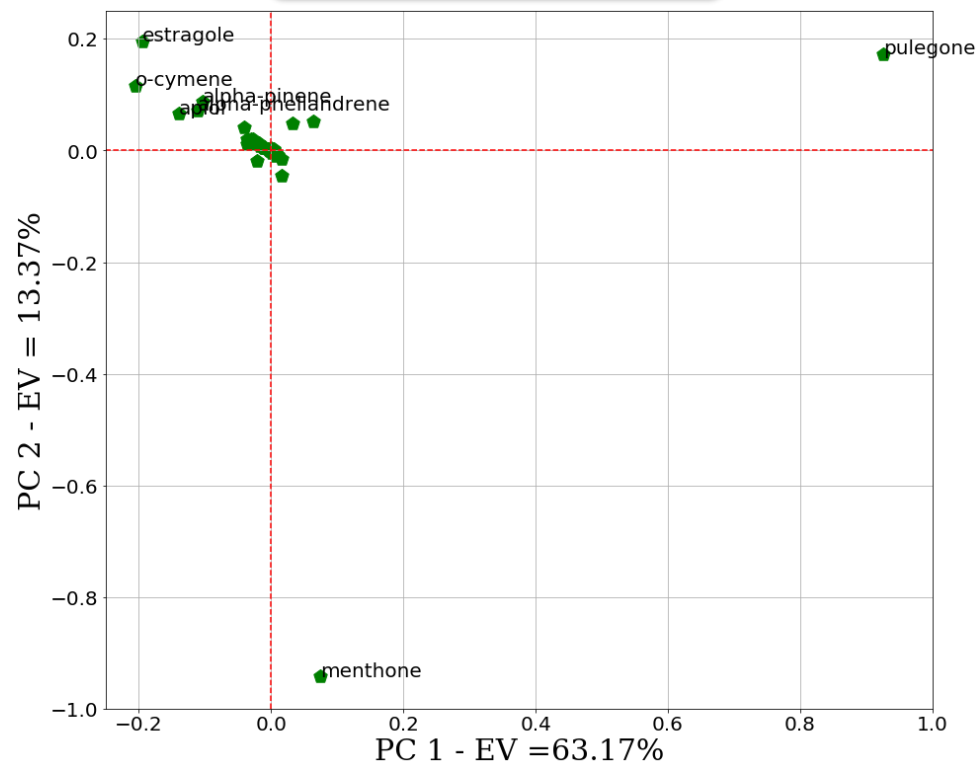
PCA

by www.rcmd.it

- Two different cluster;
- *Foeniculum Vulgare* more similar to *Ridolfia* than *Calamintha nepeta*;
- *Calamintha Nepeta* rich in Pulegone;



Loading Plot

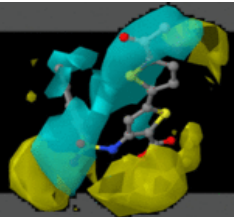




Biological Data

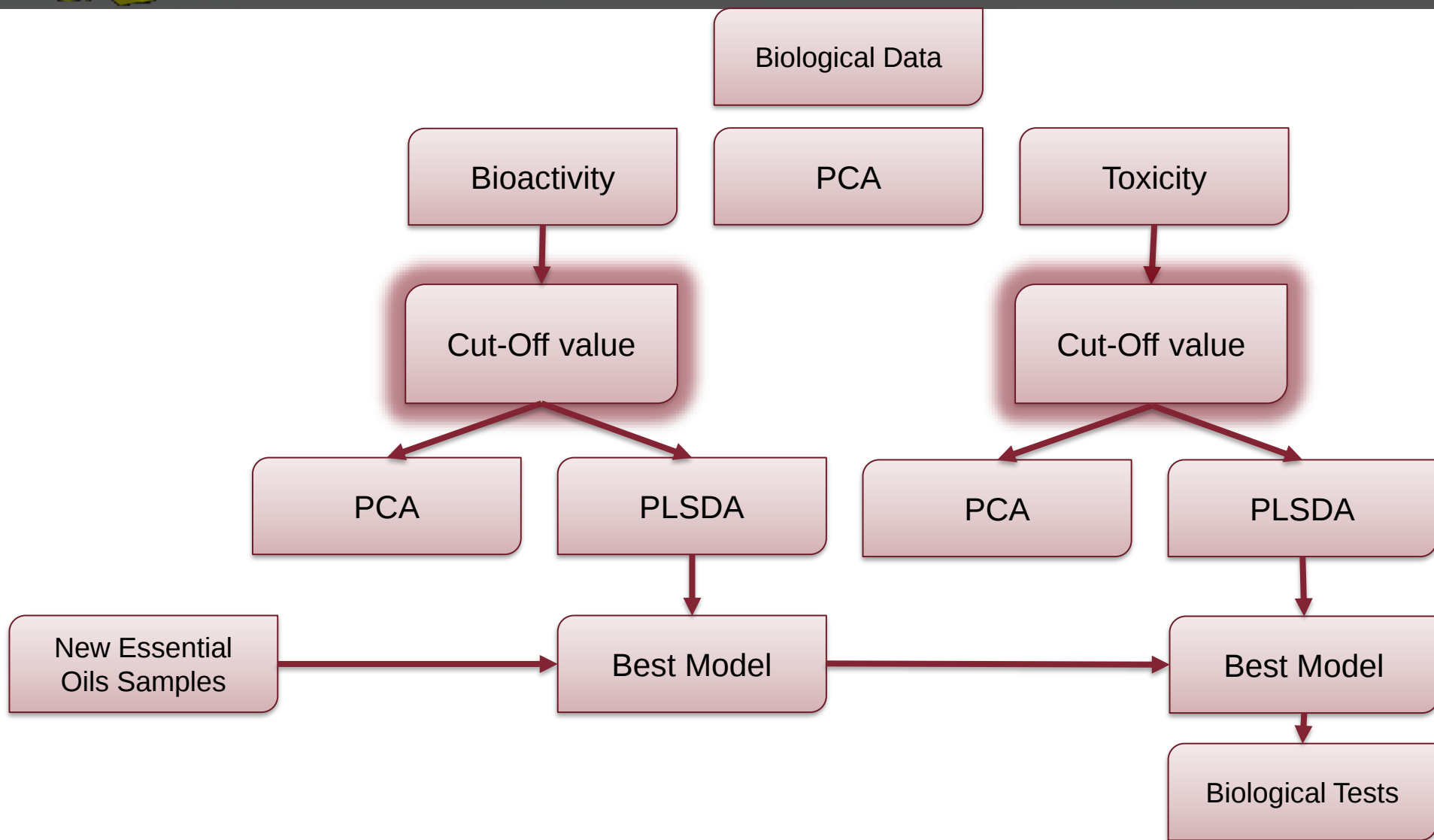
by www.rcmd.it

Sample	IC50 (mg/ml)	CC50 (mg/ml)	Sample	IC50 (mg/ml)	CC50 (mg/ml)	Sample	IC50 (mg/ml)	CC50 (mg/ml)
CS1	0,14	2,5	CJM1	0,328	2,50	FO3	0,6465	1,02
CS2	0,2063	2,9	CJM5	0,1353	3,14	FO6	0,54025	1,694
CS3	0,231	2,68	CA1	0,1617	2,84	FO24	0,1765	0,355
CS6	0,213	2,66	CA2	0,1517	4,71	FOM3	0,582	1,7
CSM1	0,174	2,00	CA3	0,175	2,50	RJ6	0,431	0,405
CMS3	0,236	2,12	CA6	0,142	1,14	RJ24	0,18075	0,36
CSM5	0,1225	1,93	CAM1	0,202	2,65	RJM4	0,295	0,9
CO1	0,21	2,50	CAM3	0,1537	3,00	RJM6	0,2	0,33
CO2	0,332	4,60	CAM5	0,4395	1,10			
CO6	0,174	2,22	FA2	0,1495	1,45			
COM1	0,282	2,76	FA6	0,1605	1,815			
COM3	0,3125	1,99	FS1	0,1945	1,005			
COM5	0,3645	2,46	FS2	0,192	0,31			
CJ1	0,2725	2,15	FS6	0,192	1,513			
CJ2	0,135	4,67	FO1	0,7235	1,513			



Overflow

by www.RCMD.it

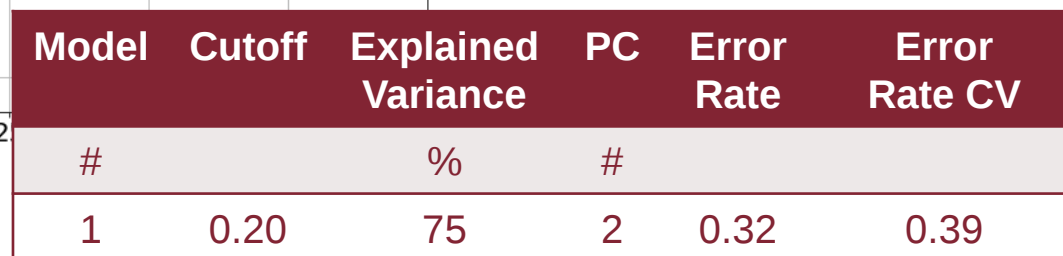




Biological Data

by www.rcmd.it

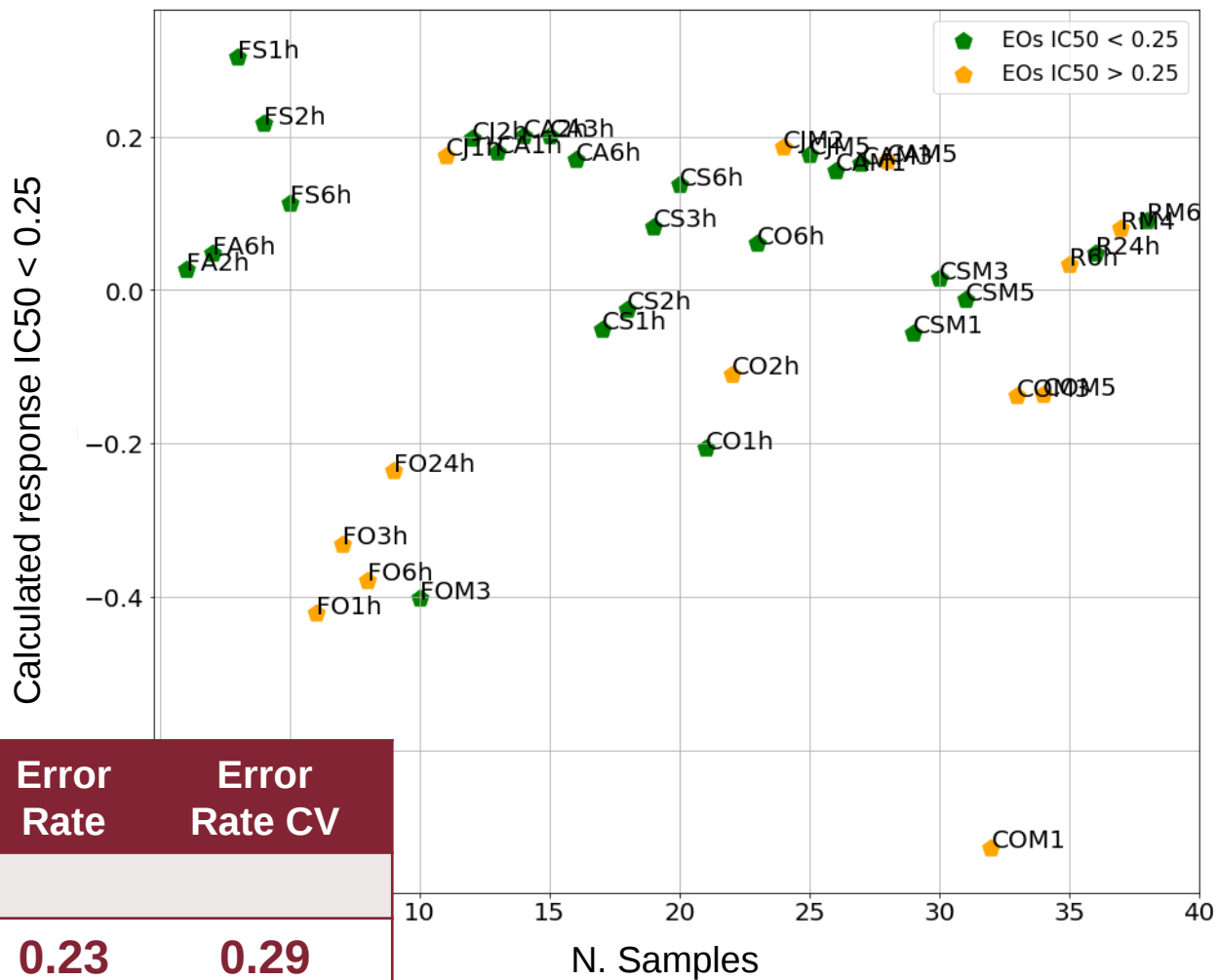
Sample	IC50 (mg/ml)	CC50 (mg/ml)	Sample	IC50 (mg/ml)	CC50 (mg/ml)	Sample	IC50 (mg/ml)	CC50 (mg/ml)
CS1	0,14	2,5	CJM1	0,328	2,50	FO3	0,6465	1,02
CS2	0,2063	2,9	CJM5	0,1353	3,14	FO6	0,54025	1,694
CS3	0,231	2,68	CA1	0,1617	2,84	FO24	0,1765	0,355
CS6	0,213	2,66	CA2	0,1517	4,71	FOM3	0,582	1,7
CSM1	0,174	2,00	CA3	0,175	2,50	RJ6	0,431	0,405
CMS3	0,236	2,12	CA6	0,142	1,14	RJ24	0,18075	0,36
CSM5	0,1225	1,93	CAM1	0,202	2,65	RJM4	0,295	0,9
CO1	0,21	2,50	CAM3	0,1537	3,00	RJM6	0,2	0,33
CO2	0,332	4,60	CAM5	0,4395	1,10	MEDIAN	0,20	2,06
CO6	0,174	2,22	FA2	0,1495	1,45			
COM1	0,282	2,76	FA6	0,1605	1,815			
COM3	0,3125	1,99	FS1	0,1945	1,005			
COM5	0,3645	2,46	FS2	0,192	0,31			
CJ1	0,2725	2,15	FS6	0,192	1,513			
CJ2	0,135	4,67	FO1	0,7235	1,513			





PLSDA on Biological Data

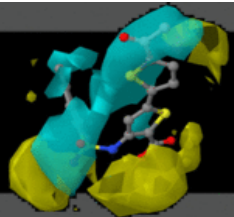
by www.RCMD.it



Calculated response IC50 < 0.25

N. Samples

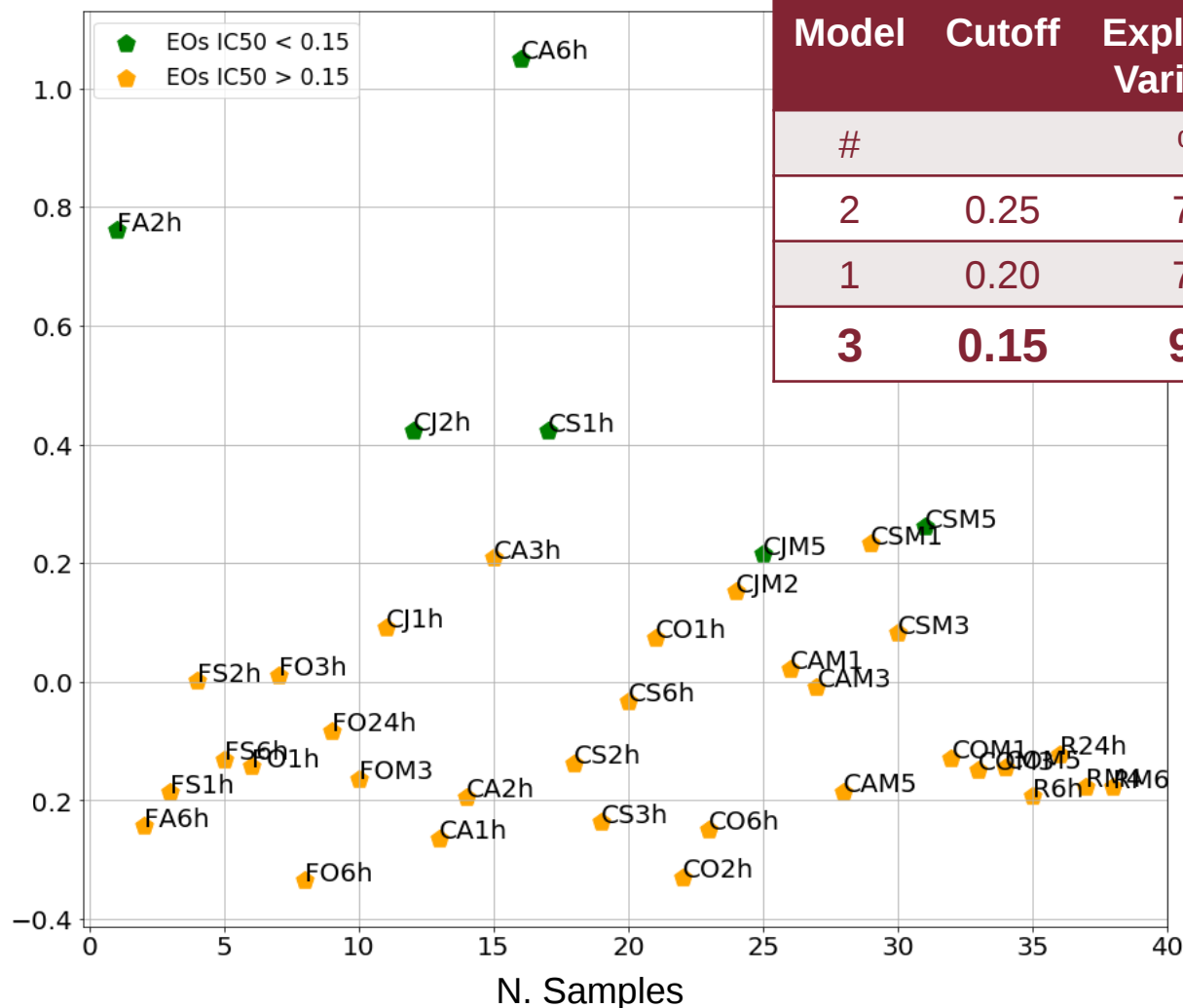
Model	Cutoff	Explained Variance	PC	Error Rate	Error Rate CV
#		%	#		
2	0.25	75	2	0.23	0.29
1	0.20	75	2	0.32	0.39



PLSDA on Biological Data

by www.RCMD.it

Calculated response IC50 < 0.15



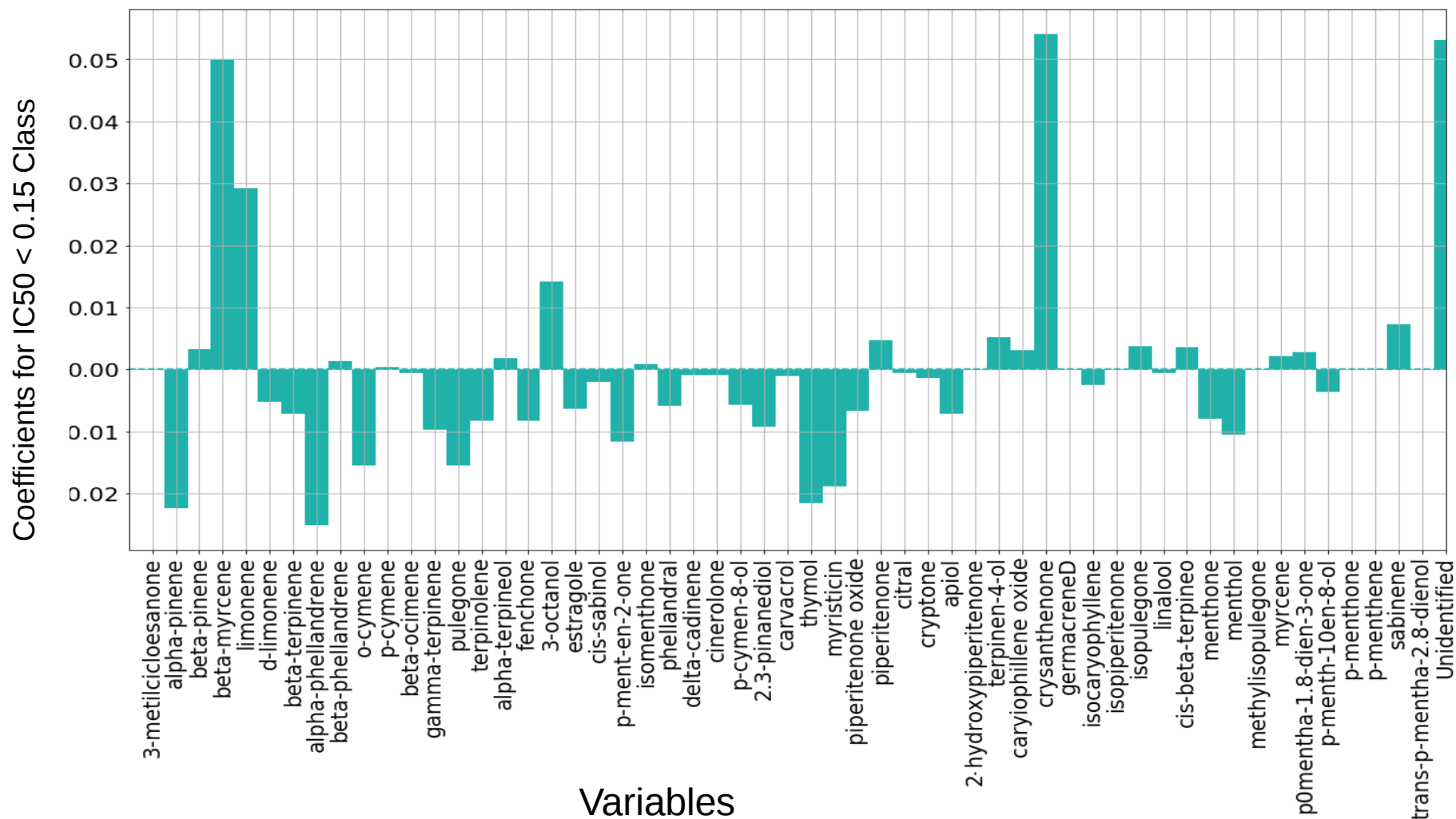
Model	Cutoff	Explained Variance	PC	Error Rate	Error Rate CV
#		%	#		
2	0.25	75	2	0.23	0.29
1	0.20	75	2	0.32	0.39
3	0.15	98	7	0.03	0.15

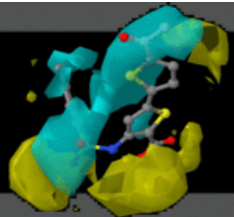


Variable Coefficients

-Biological Model

by www.RCMD.it

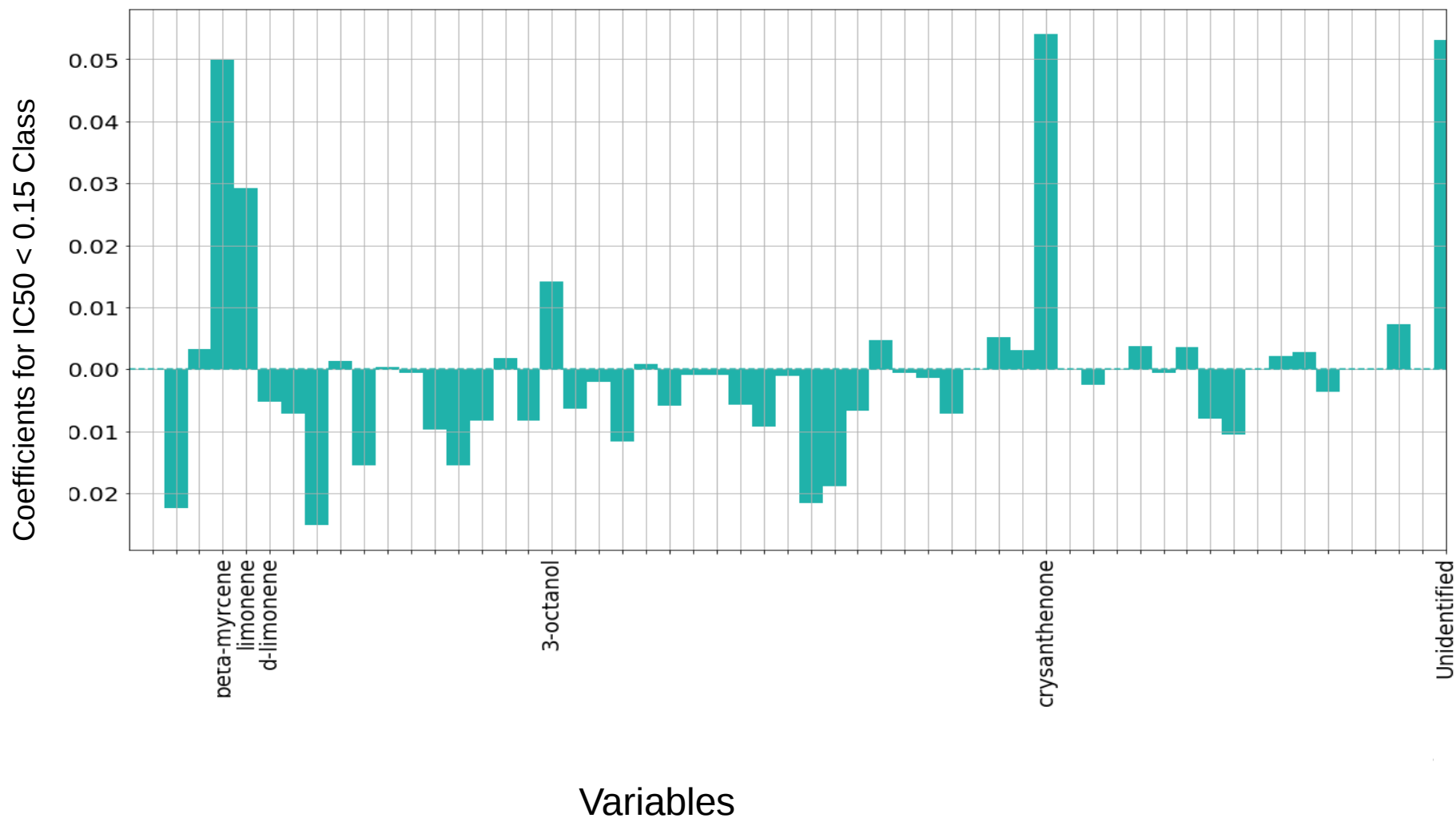




Variable Coefficients

-Biological Model

by www.RCMD.it

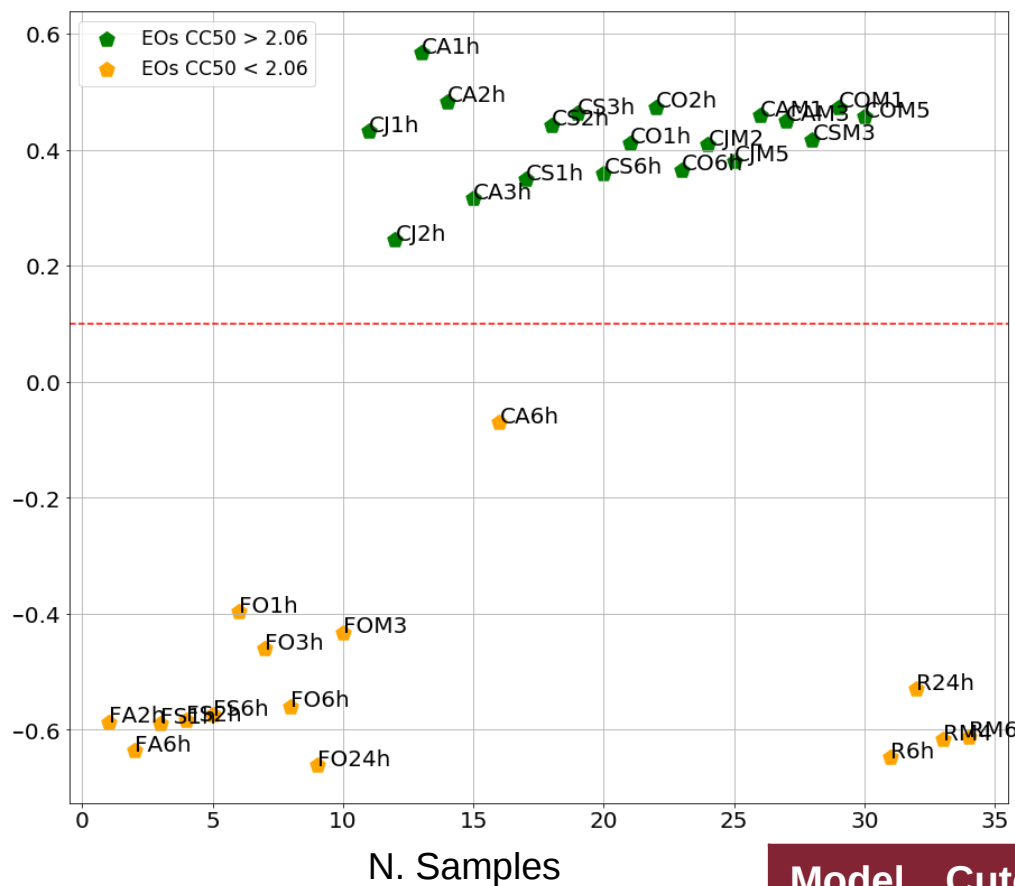




PLSDA on Toxicological Data

by www.RCMD.it

Calculated response CC50 > 2.06 Class



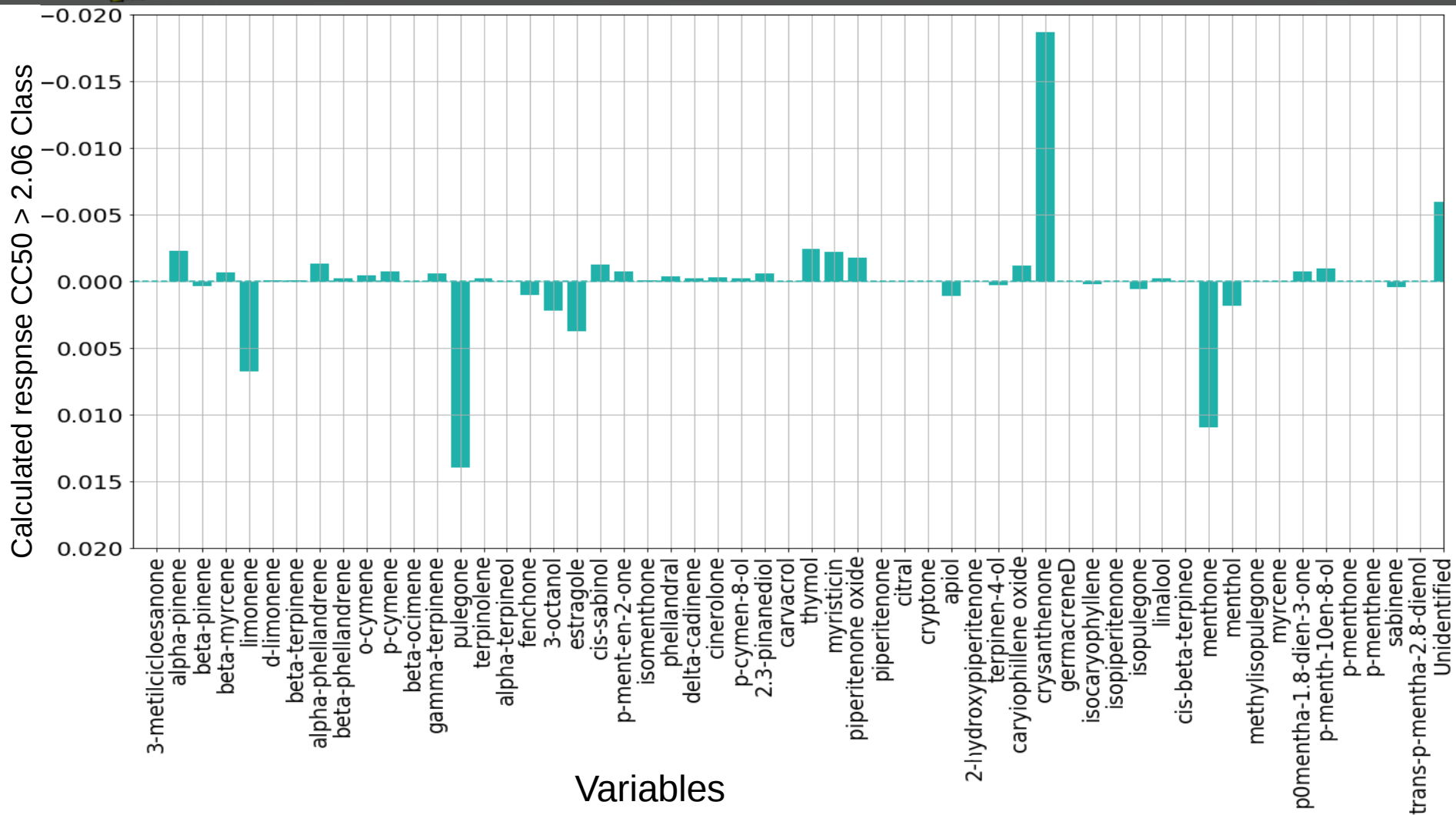
Model	Cutoff	Explained Variance	PC	Error Rate	Error Rate CV
#		%	#		
1	2	78	3	0	0.03



Variable Coefficients

-Toxicological Model

by www.RCMD.it

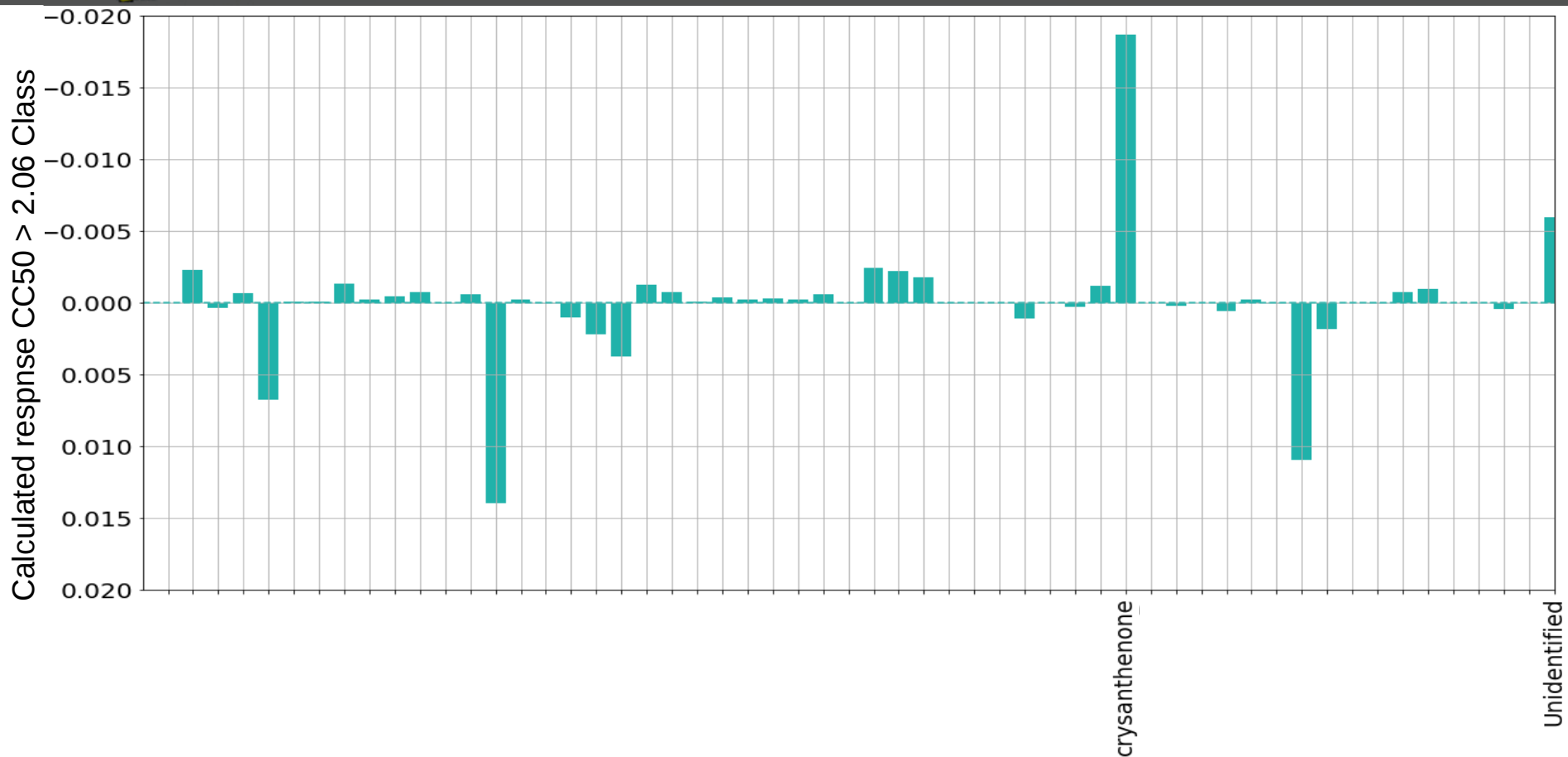


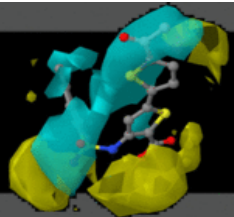


Variable Coefficients

-Toxicological Model

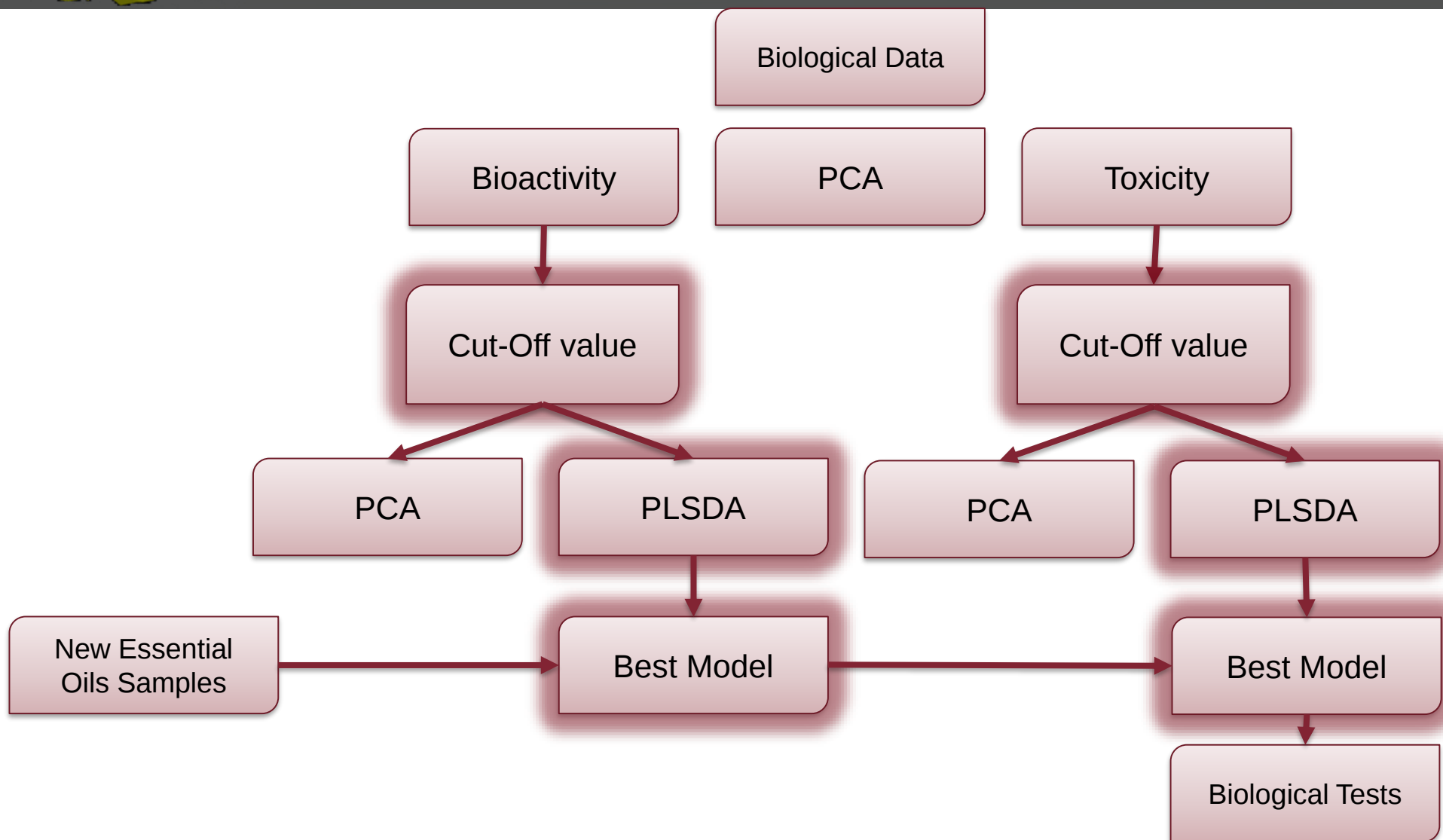
by www.RCMD.it





Overflow

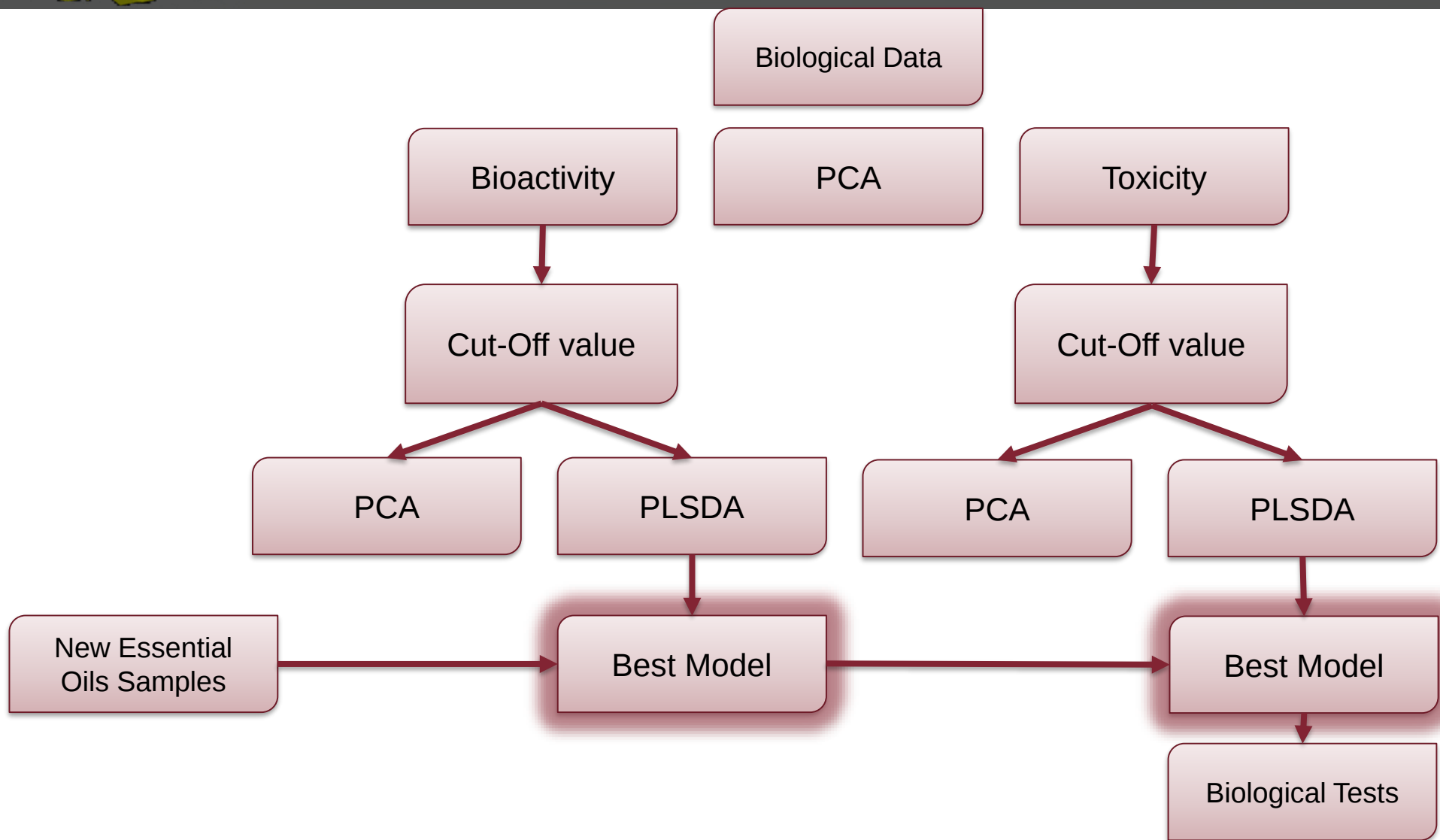
by www.RCMD.it





Overflow

by www.RCMD.it





Prediction Samples Set

by www.RCMD.it

FA1h	FAM1	FSM5	CA12h	CSM2	RJM1
FA3h	FAM2	FOM1	CA24h	CSM4	RJM2
FA12h	FAM3	FOM2	CS12h	COM2	RJM3
FA24h	FAM4	FOM4	CS24h	COM4	
FS3h	FAM5	FOM5	CJM1	RJ1h	
FS12h	FSM1	CJ3h	CJM3	RJ2h	
FS24h	FSM2	CJ6h	CJM4	RJ3h	
FO2h	FSM3	CJ12h	CAM2	RJ12h	
FO12h	FSM4	CJ24h	CAM4	RJ30h	



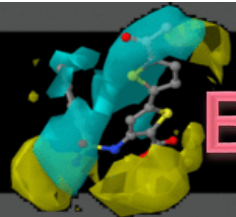
Calamintha Nepeta



Foeniculum Vulgare

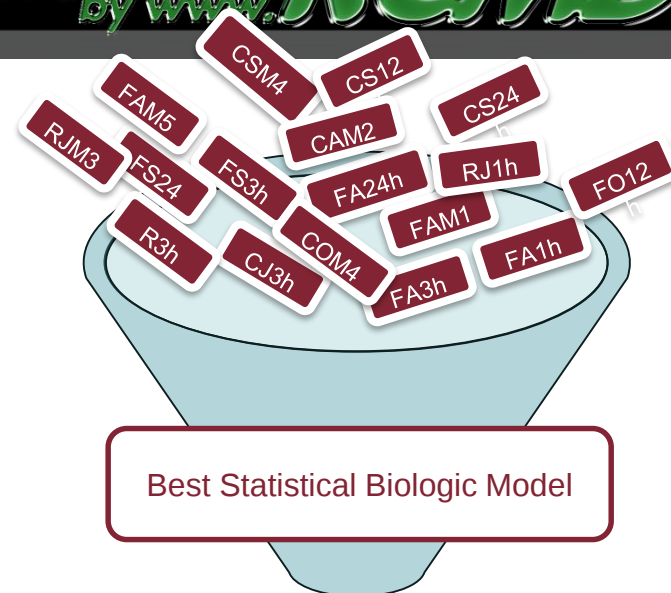


Ridolfia segetum



Biological Activity Prediction

by www.rcmd.it

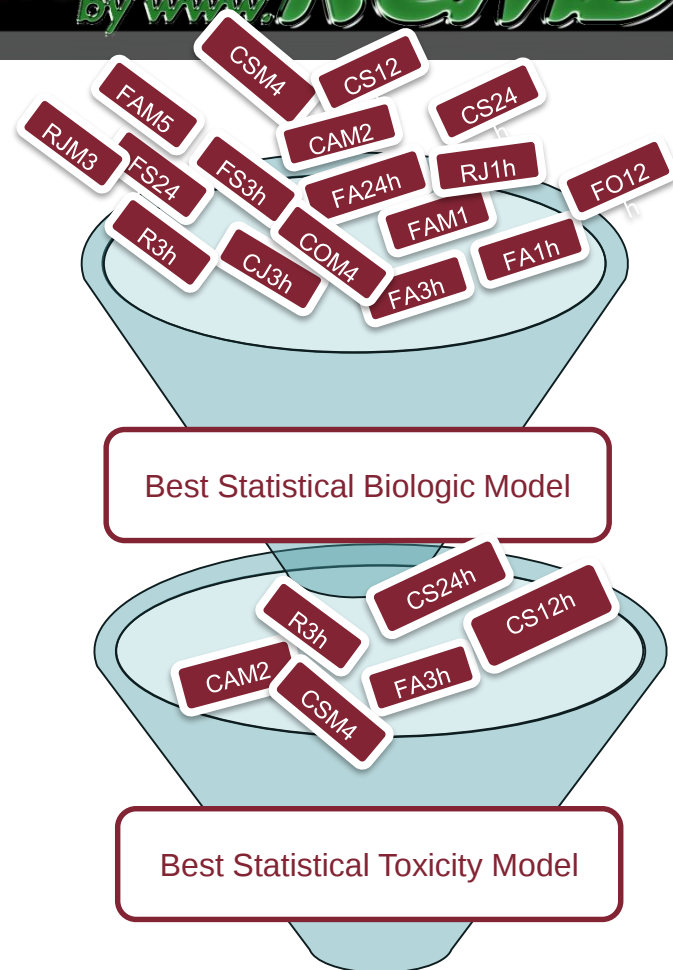
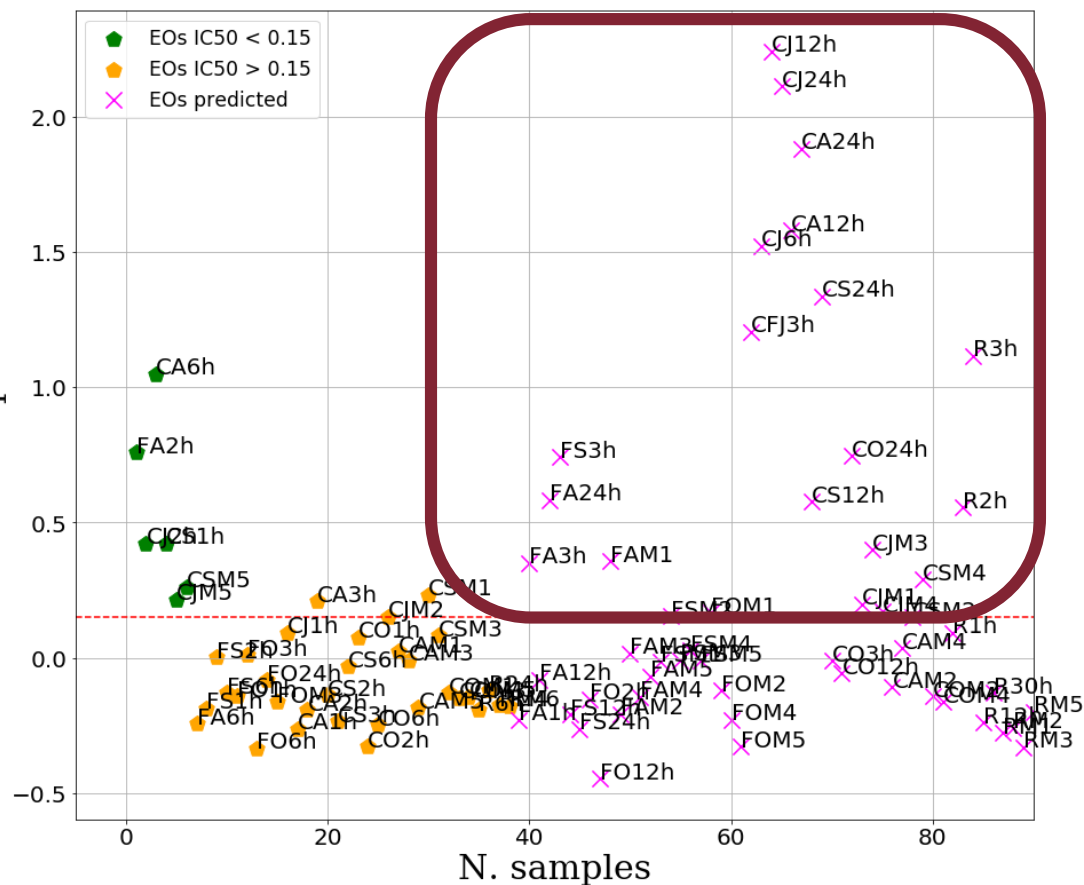




Biological Activity Prediction

by www.rcmd.it

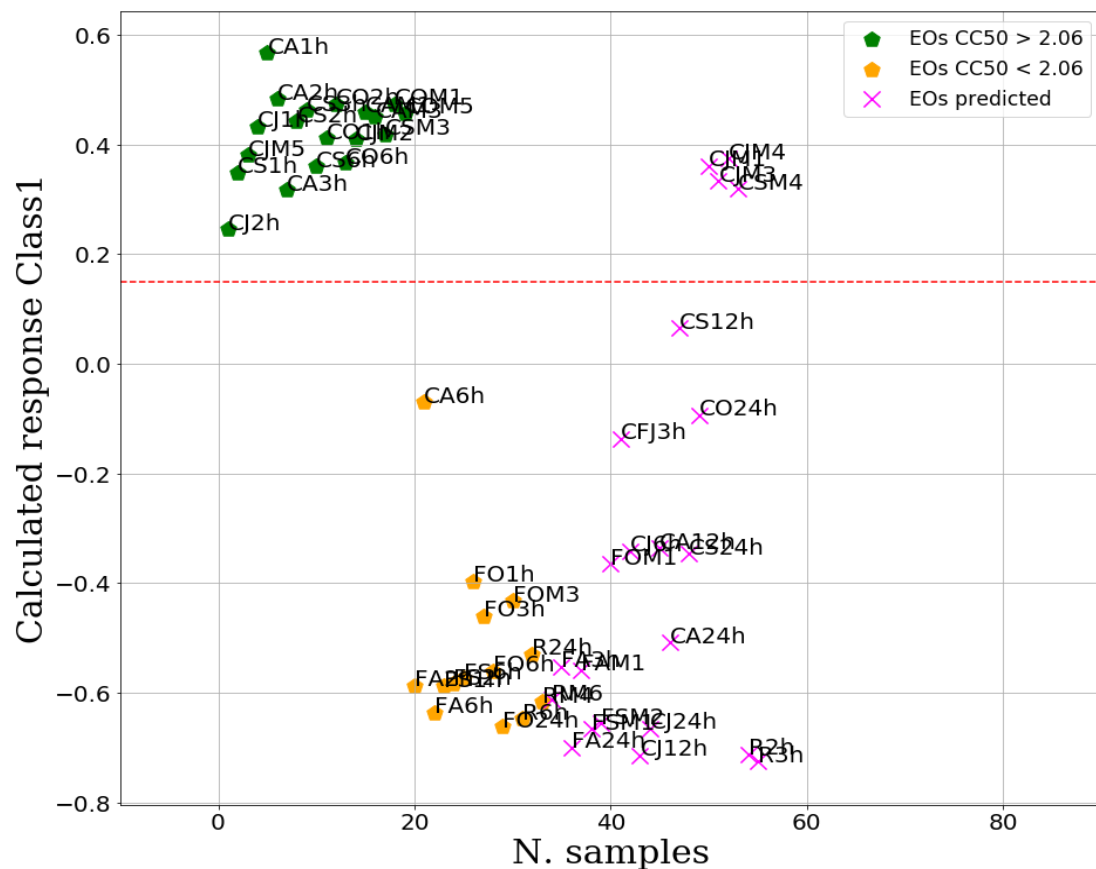
Calculated response Class1





Toxicity Prediction

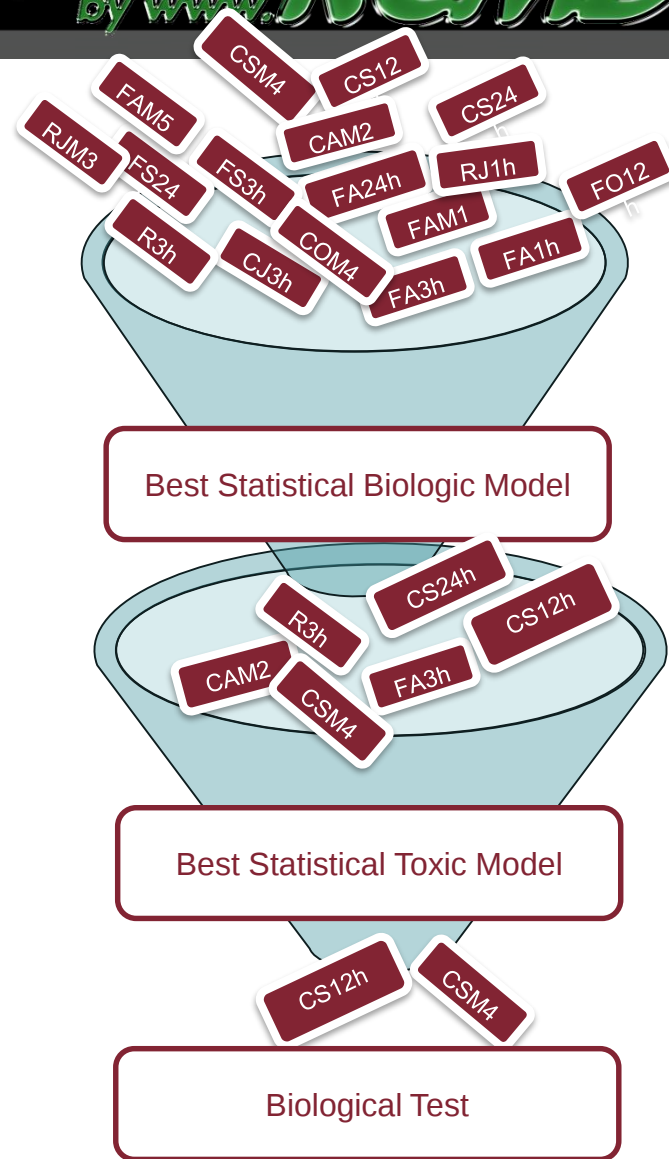
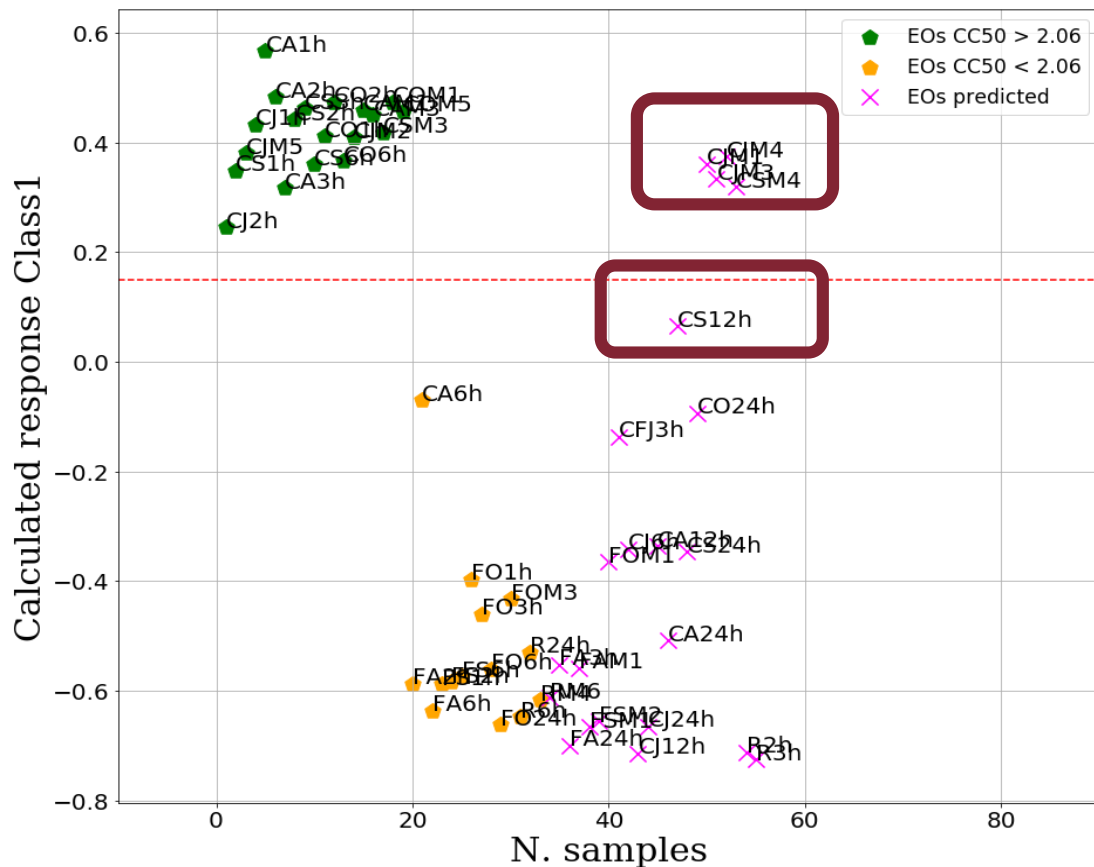
by www.rcmd.it

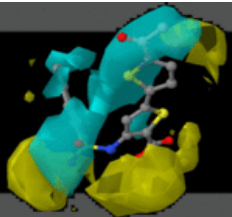




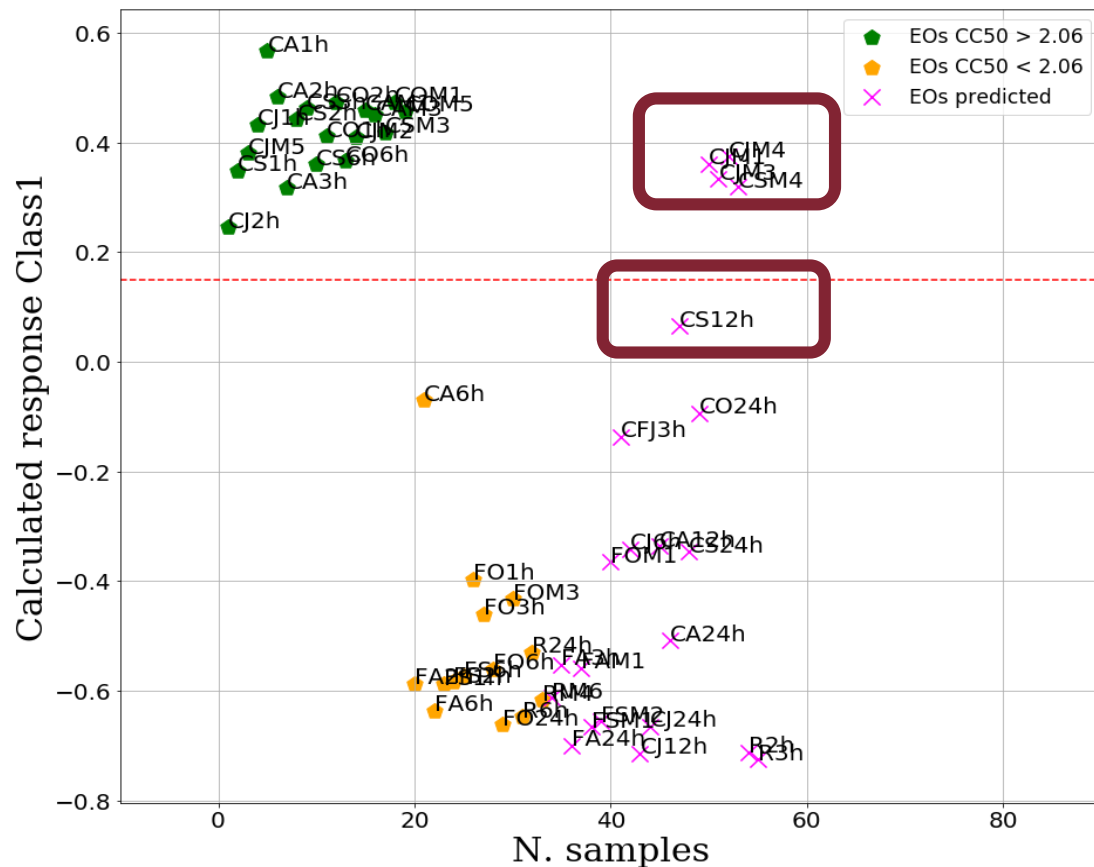
Toxicity Prediction

by www.rcmd.it

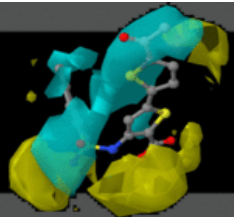




Biological Results



Sample	IC50 (mg/ml)	CC50 (mg/ml)
CJM1	0.063	>3.0
CJM3	0.116	>3.0
CJM4	0.124	>3.0
CS12	0.143	2.50
CSM4	0.460	0.52



Conclusion

by www.RCMD.it

- It was showed as Machine Learning techniques are usefull to study and analyse also chemical complex mixtures;
- Using Machine Learning techniques was developed a scientific protocol;
- Applying this presented protocol were identified a Essential Oils with promising biological activity against Herpes Simplex Virus;

Rational Design of Potential Novel Pharmaceutical Compounds Through Computational Approaches and Machine Learning Techniques.



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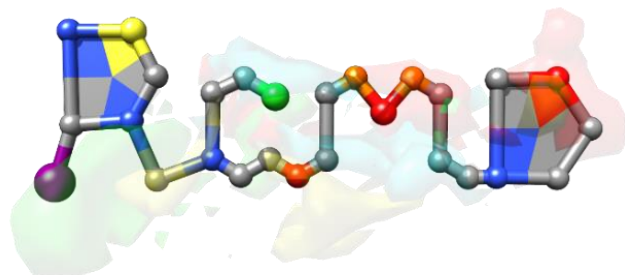
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