

SBDD



SAPIENZA
UNIVERSITÀ DI ROMA



Download Ligand Scout



Linux:

https://www.inteligand.com/ligandscout4/downloads/LigandScout_4_4_5_linux64_20200714.tar.gz

Windows:

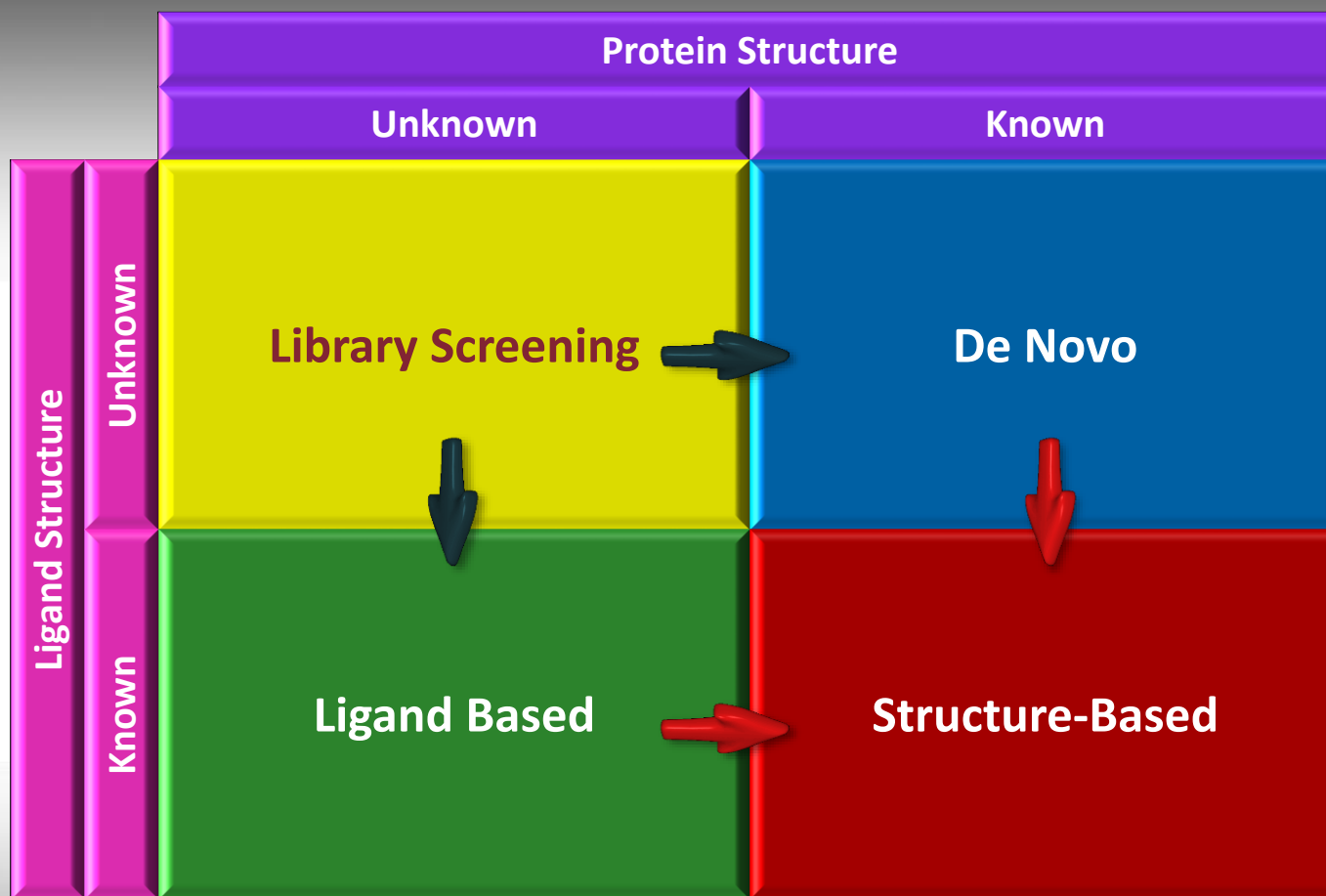
https://www.inteligand.com/ligandscout4/downloads/LigandScout_4_4_5_win64_20200714.exe

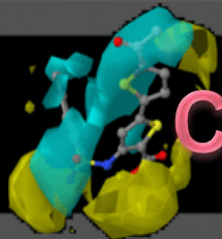
Mac:

https://www.inteligand.com/ligandscout4/downloads/LigandScout_4_4_5_macos_20200714.dmg

LICENZA:

67130137638922548398





CADD methods in Drug Design

Ligand-Based

QSAR

Pharmacophore

3-D QSAR

Structure-Based

**Scoring
Function
Docking**

COMBINE





SBDD methods

Structure-Based Drug Design Approaches

3-D QSAR (Molecules aligned by SB methods)

Scoring Function (A Sort of QSARs for Molecular Docking)

COMBINE (A Full SB 3-D QSAR)

Proteochemometric (A QSAR SB derived method)

Molecular Dynamics

Pharmacophoric Approaches (Using Targets Structures)

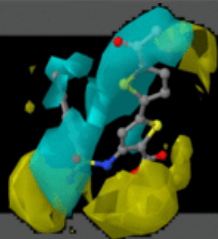
Homology Modeling (To Build Target Structures)



SB 3-D QSAR



**3-D QSAR models developed with
molecular alignment rules employing
3-D structure of the target**



SB 3-D QSAR

ACS Publications
MOST TRUSTED. MOST CITED. MOST READ.

Publications A-Z Home | Auth

Search

J. Chem. In

Journal of
**CHEMICAL INFORMATION
AND MODELING**

Home | Browse the Journal | Articles ASAP | Current Issue | Submission & Review | Subscribe

Article

Combining 3-D Quantitative Structure-Activity Relationship with Ligand Based and Structure Based Alignment Procedures for *in Silico* Screening of New Hepatitis C Virus NS5B Polymerase Inhibitors

Ira Musmuca ¹, Antonia Caroli ¹, Antonello Mai ¹, Neerja Kaushik-Basu ¹, Payal Arora ¹ and Rino Ragno ¹

Istituto Pasteur-Fondazione Cenci Bolognetti, Dipartimento di Chimica e Tecnologie del Farmaco, Sapienza Università di Roma, P. le A. Moro 5, 00185, Rome, Italy and Department of Biochemistry and Molecular Biology, UMDNJ-New Jersey Medical School, 185 South Orange Avenue, Newark, NJ

Abstract

Full Text HTML

Hi-Res PDF [3594 KB]

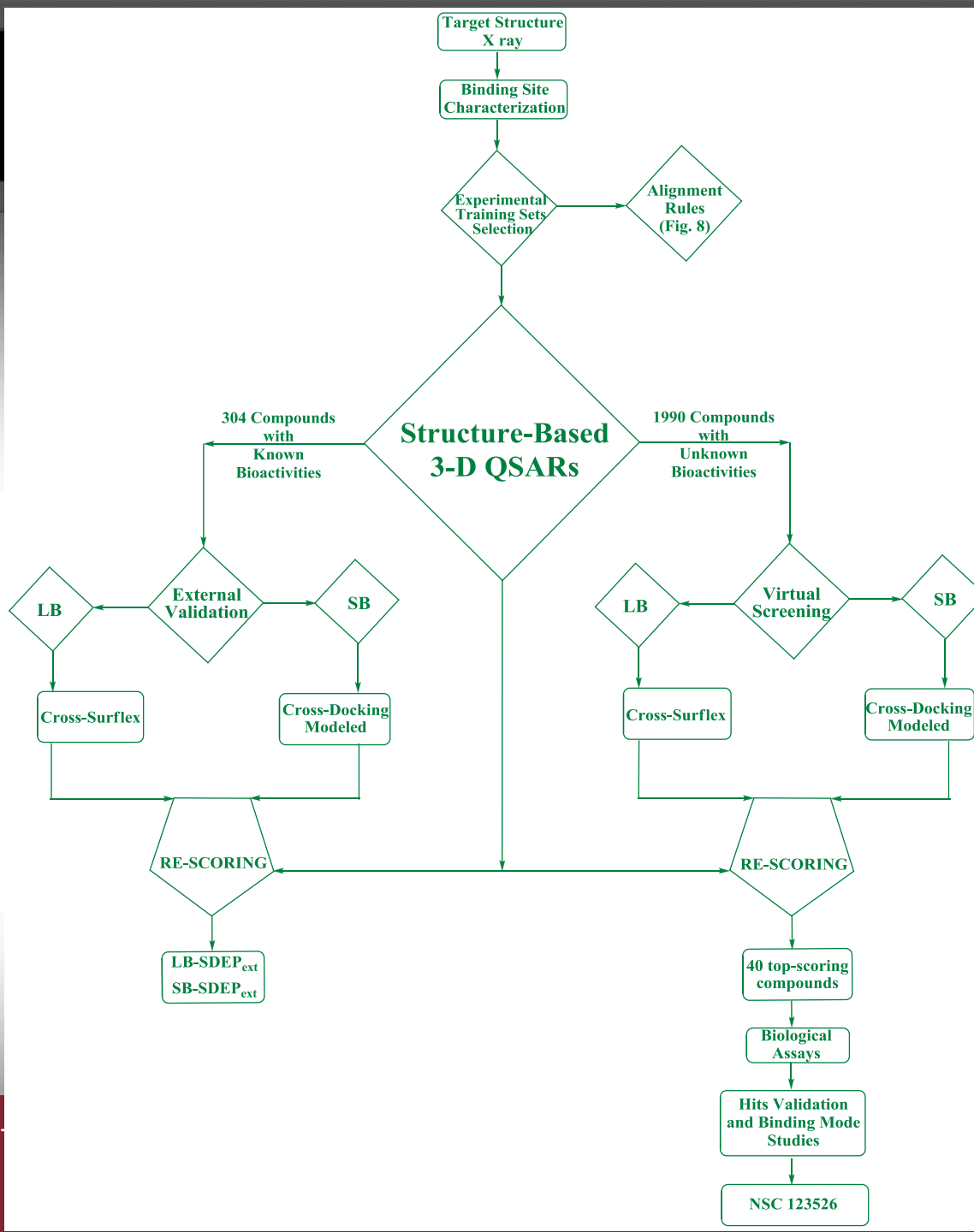
PDF w/ Links [602 KB]

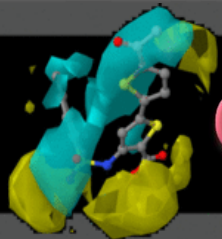
Supporting Info ->

Figures **New**

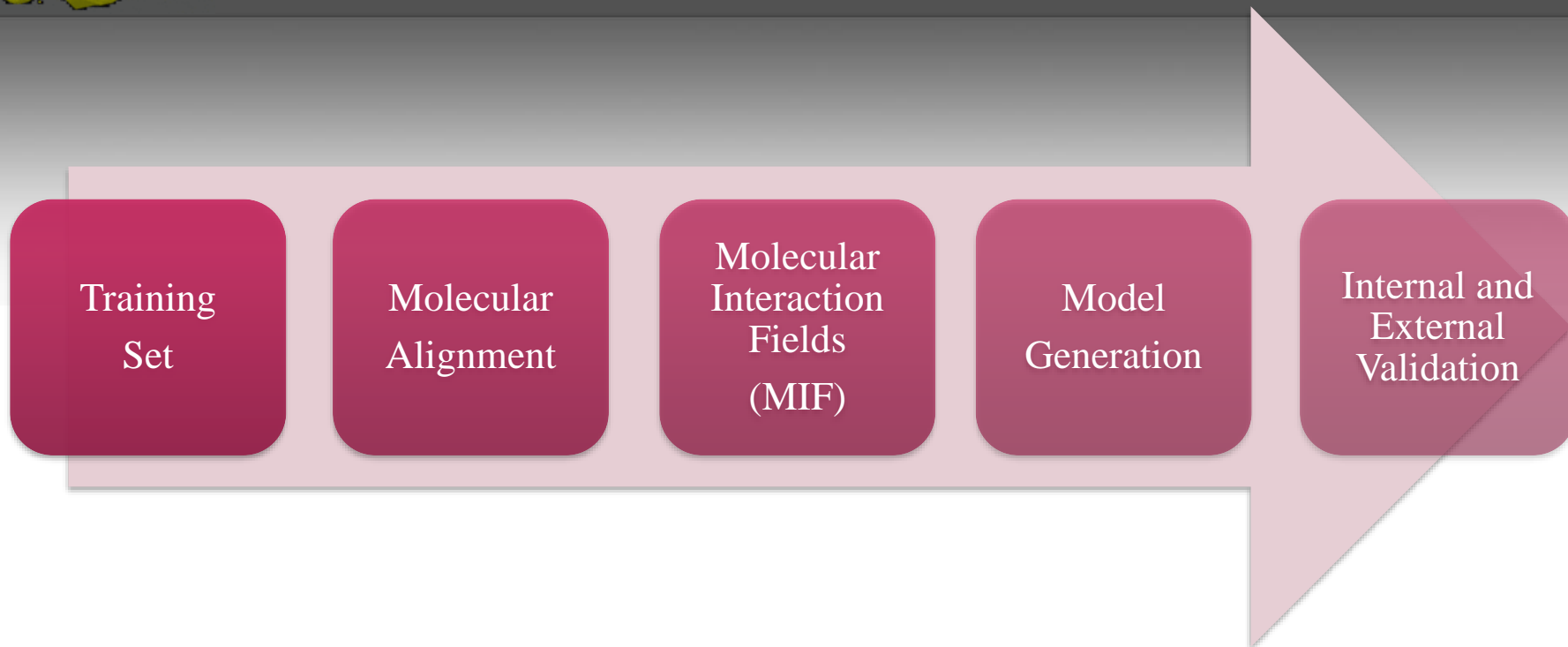
Reference Quick View

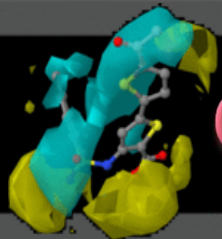
Citing Articles





CoMFA/3-D QSAR Procedure





CoMFA/3-D QSAR Procedure

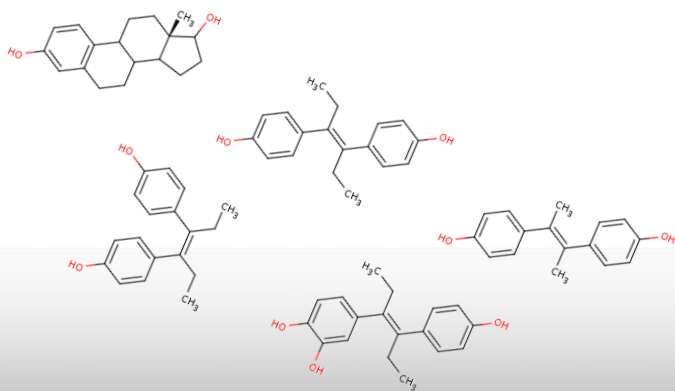
**Training
Set**

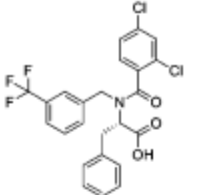
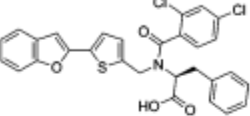
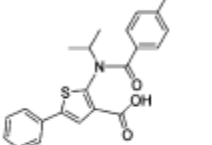
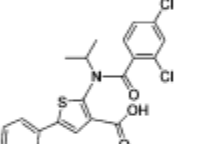
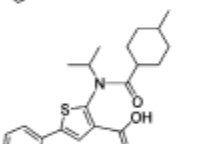
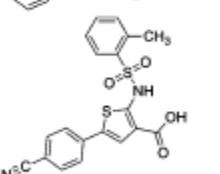
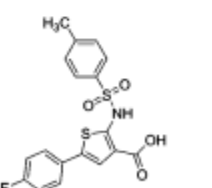
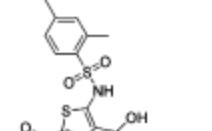
Molecular
ligment

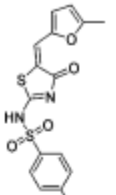
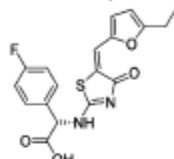
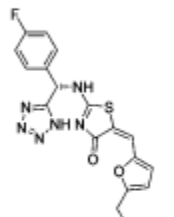
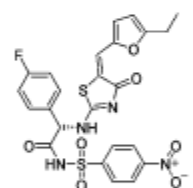
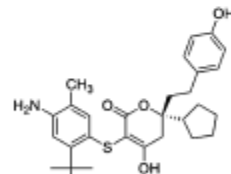
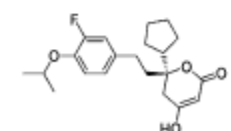
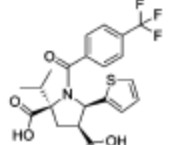
Molecular
Interaction
Fields
(MIF)

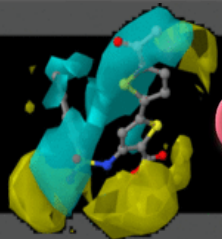
Model
Generation

Internal and
External
Validation

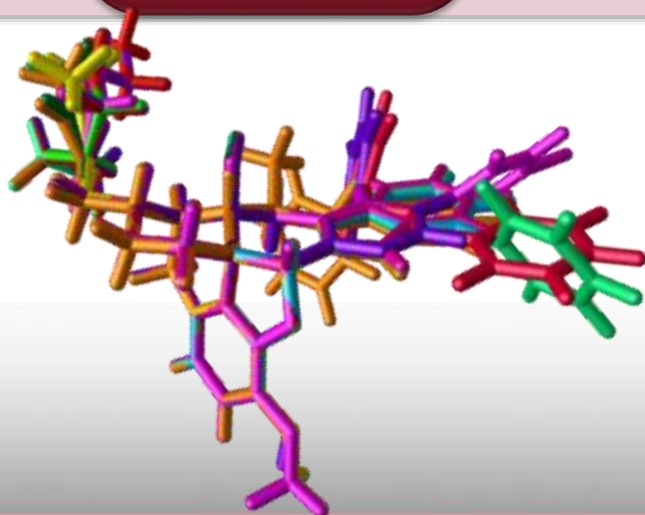
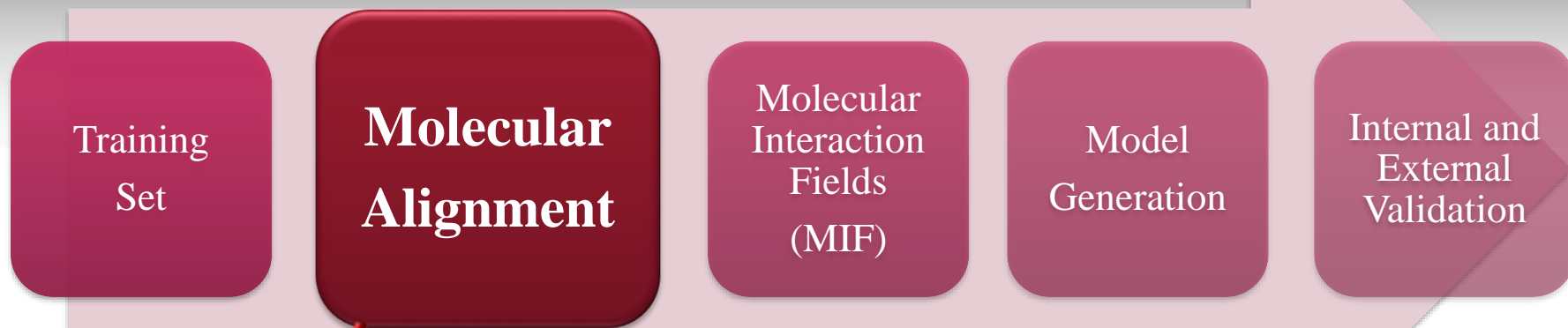


PDB Code	Ligand Name	Entry	Ligand Structure	IC ₅₀ (μM)
1NHU	(2S)-2-[(2,4-dichlorobenzoyl)-(3-trifluoromethylbenzyl)-amino]-3-phenylpropionic acid	1		1.7
1NHV	(2S)-2-[(5-benzofuran-2-ylmethyl)-(2,4-dichlorobenzoyl)-amino]-3-phenylpropionic acid	2		8.6
1YVX	3-[isopropyl(4-methylbenzoyl)amino]-5-phenylthiophene-2-carboxylic acid	3		8.0
1YVZ	3-[(2,4-dichlorobenzoyl)(isopropyl)amino]-5-phenylthiophene-2-carboxylic acid	4		4.4
2GIR	3-[isopropyl[(trans-4-methylcyclohexyl)carbonyl]amino]-5-phenylthiophene-2-carboxylic acid	5		1.5
2D3U	5-(4-cyanophenyl)-3-[(2-methylphenyl)sulfonyl]amino}thiophene-2-carboxylic acid	6		0.2663
2D3Z	5-(4-fluorophenyl)-3-[(4-methylphenyl)sulfonyl]amino}thiophene-2-carboxylic acid	7		0.2918
2D41	5'-acetyl-4-[[2,4-dimethylphenyl)sulfonyl]amino]-2,2'-bithiophene-5-carboxylic acid	8		0.3073

PDB Code	Ligand Name	Entry	Ligand Structure	IC ₅₀ (μM)
2HWH	4-methyl-N-[(5E)-5-[(5-methyl-2-furyl)methylene]-4-oxo-4,5-dihydro-1,3-thiazol-2-yl]benzenesulfonamide	9		2.0
2HWI	(2S)-[[(5Z)-5-[(5-ethyl-2-furyl)methylene]-4-oxo-4,5-dihydro-1,3-thiazol-2-yl)amino](4-fluorophenyl)acetic acid	10		3.0
2IIR	(5Z)-5-[(5-ethyl-2-furyl)methylene]-2-[[[(S)-(4-fluorophenyl)(1H-tetrazol-5-yl)methyl]amino]-1,3-thiazol-4(5H)-one	11		9.7
2O5D	(2S)-2-([[(5Z)-5-[(5-ethyl-2-furyl)methylene]-4-oxo-4,5-dihydro-1,3-thiazol-2-yl)amino]-2-(4-fluorophenyl)-N-[(4-nitrophenyl)sulfonyl]acetamide	12		7.0
1O5S	3-(4-amino-2-tert-butyl-5-methyl-phenylsulfanyl)-6-cyclopentyl-4-hydroxy-6-[2-(4-hydroxy-phenyl)-ethyl]-5,6-dihydro-pyran-2-one	13		0.93
2HAI	(6S)-6-cyclopentyl-6-[2-(3-fluoro-4-isopropoxyphenyl)ethyl]-4-hydroxy-5,6-dihydro-2H-pyran-2-one	14		0.53
2JC0	(2S,4S,5R)-2-isobutyl-5-(2-thienyl)-1-[4-(trifluoromethyl)benzoyl]pyrrolidine-2,4-dicarboxylic acid	15		20.0

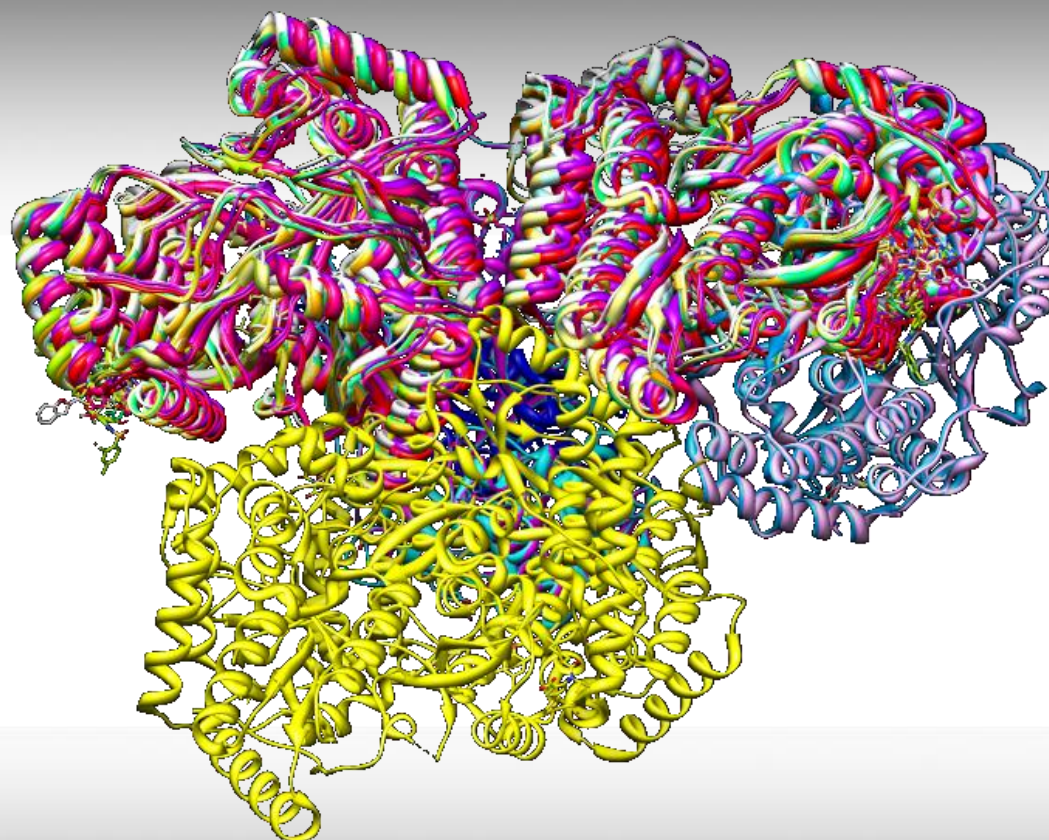


CoMFA/3-D QSAR Procedure



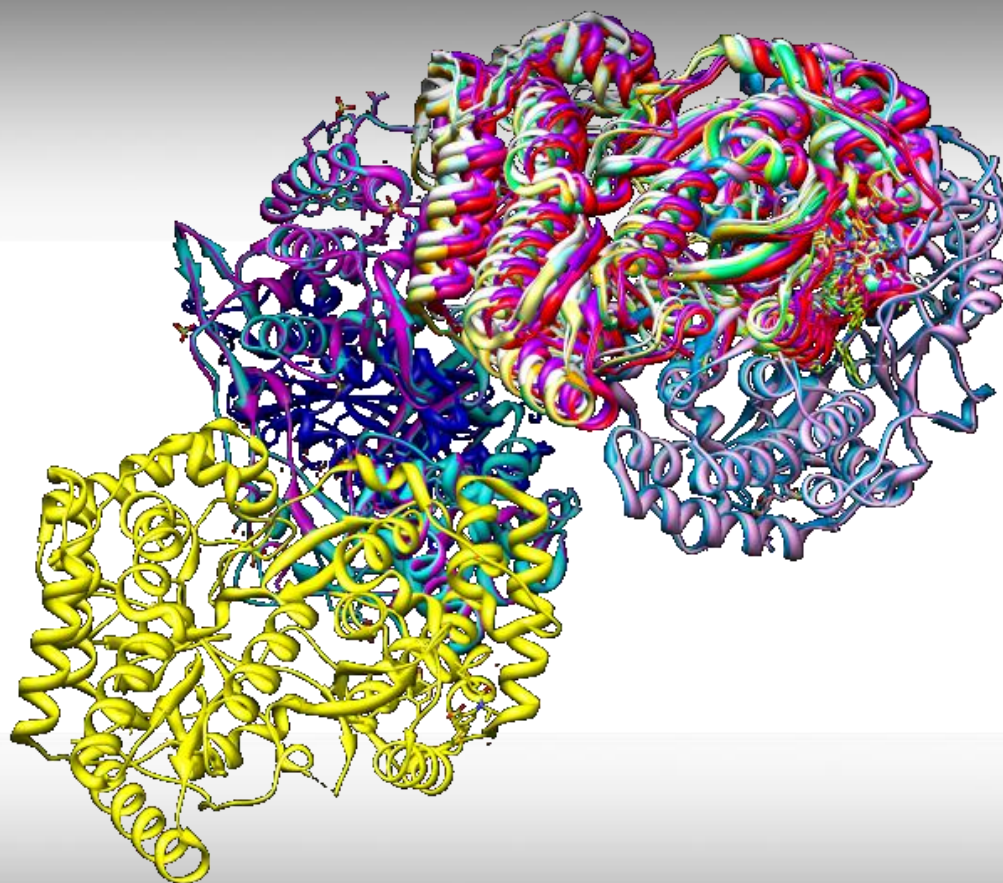


SB Alignment



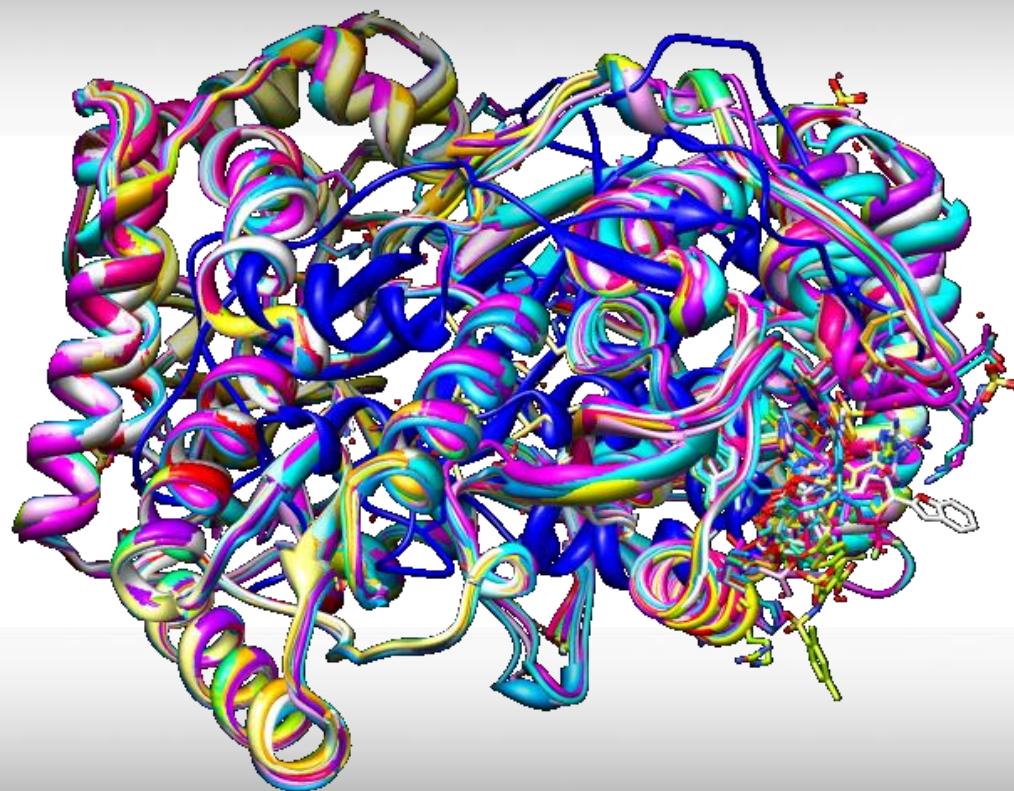


SB Alignment



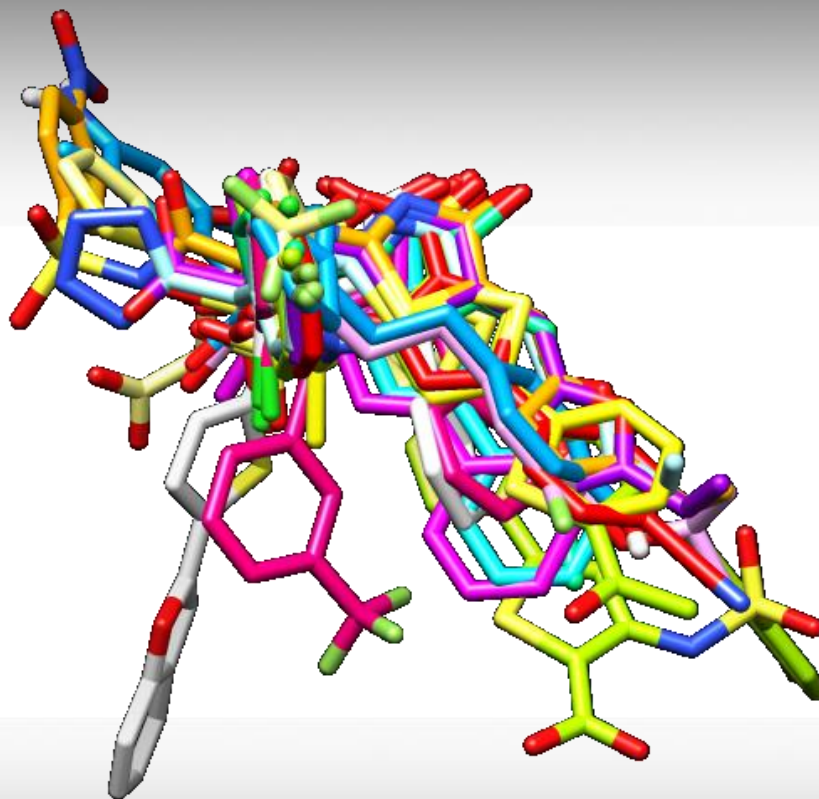


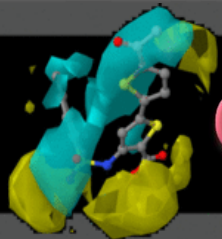
SB Alignment



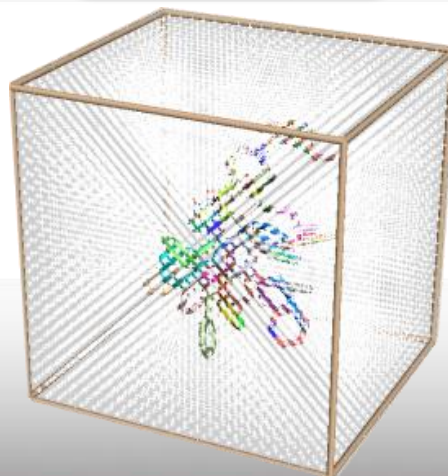
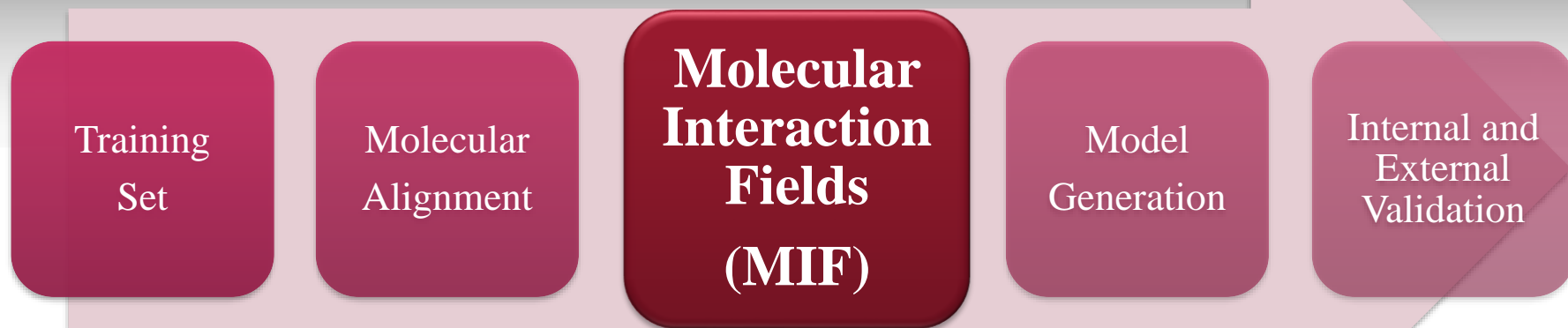


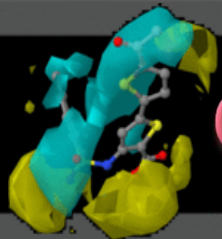
SB Alignment



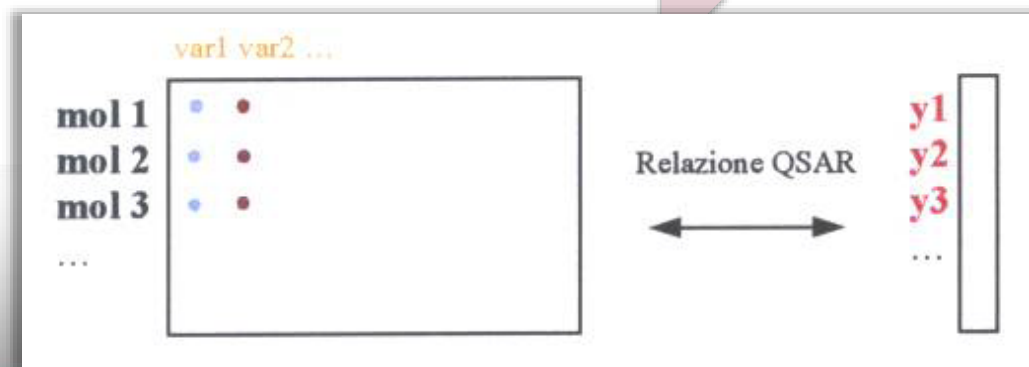
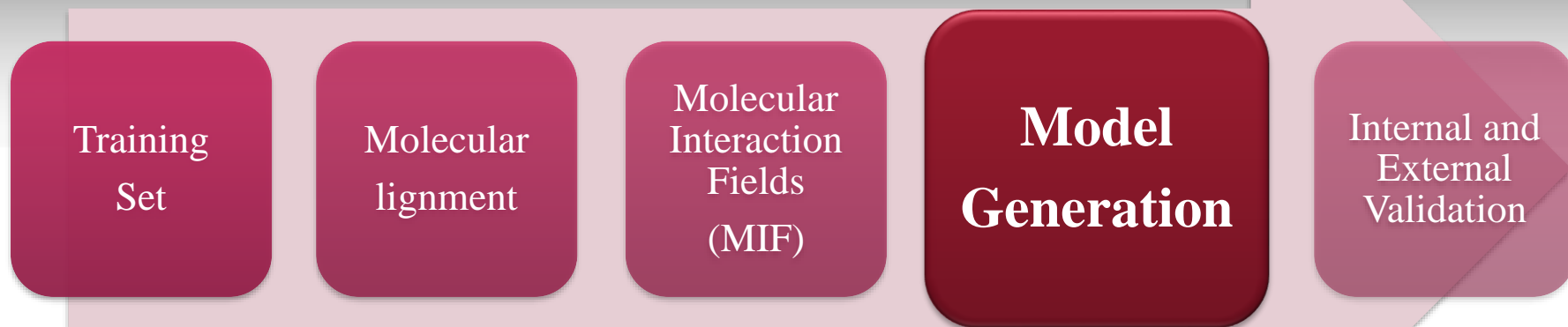


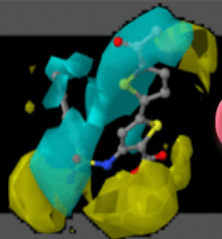
CoMFA/3-D QSAR Procedure



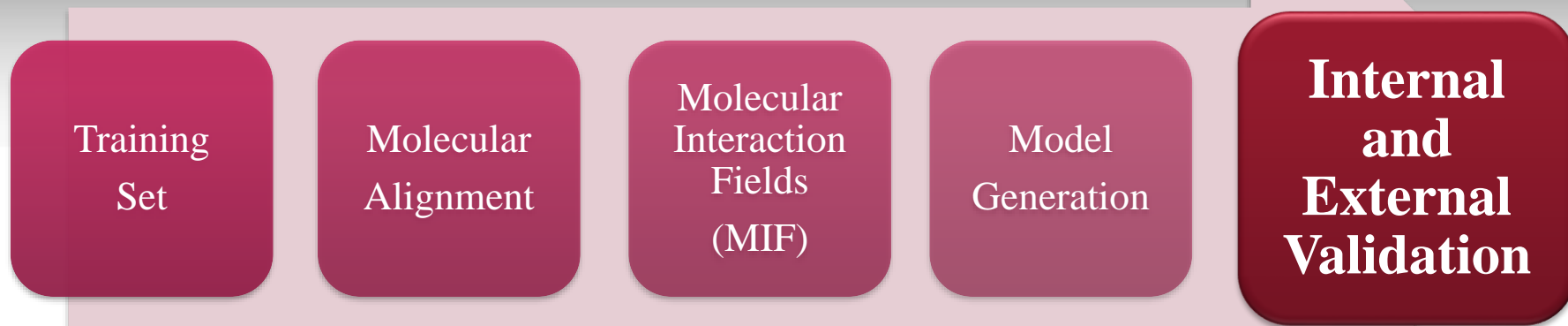


CoMFA/3-D QSAR Procedure

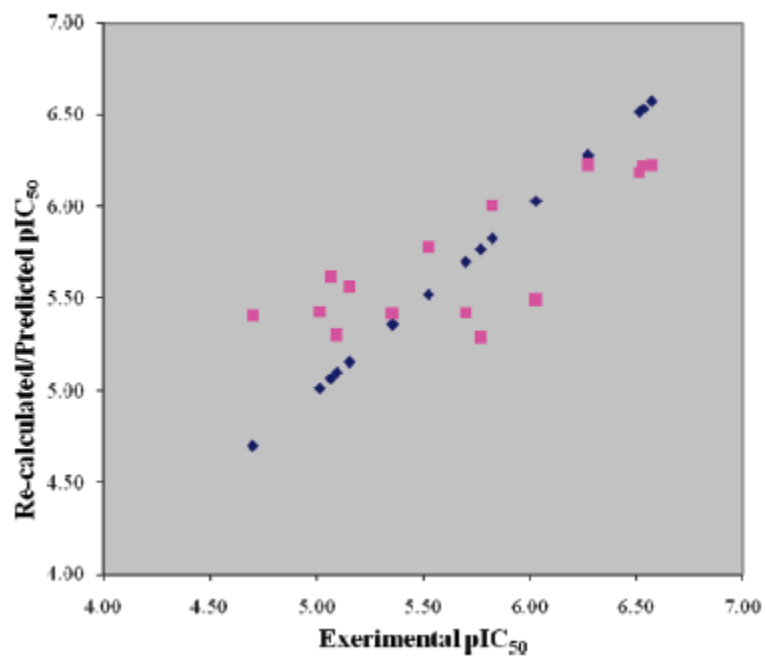
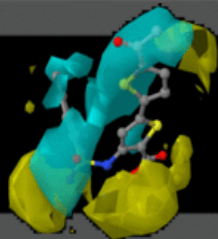




CoMFA/3-D QSAR Procedure

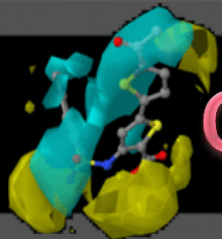


$$SDEP = \sqrt{\sum (y_{\text{exp}} - y_{\text{pred}})^2 / n - 1}$$
$$q^2 = 1 - \sum (y_{\text{exp}} - y_{\text{pred}})^2 / \sum (y_{\text{exp}} - y)^2$$



model	<i>N</i>	GRID probe	<i>V</i>	PC	r^2	q^2	SDEP _{CV-L50}
thumb training set	15	C1=	5133	3	0.99	0.69	0.31
palm training set	10	C1=	3848	3	0.99	0.55	0.66

^a *N*, number of compounds in the training set; *V*, number of GOLPE variables; PC, optimal number of principal components; r^2 , conventional square correlation coefficient; q^2 , cross-validation correlation coefficient; SDEP, cross-validated standard error of prediction using the leave-five-out cross-validation method.



CoMFA/3-D QSAR Procedure

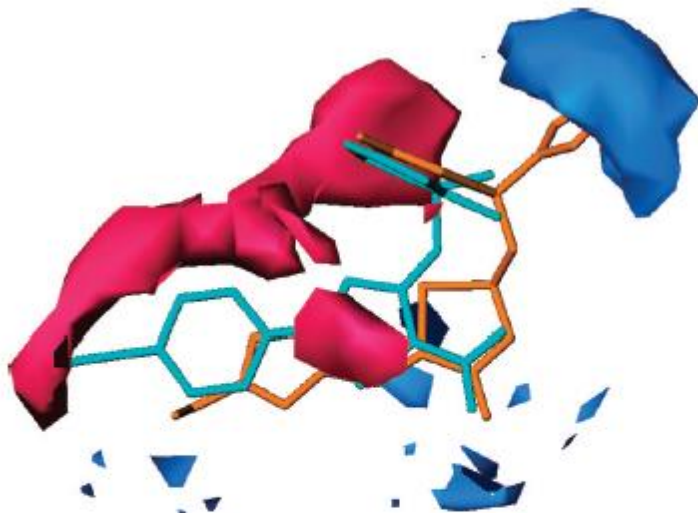


Figure 3. Contour maps of the PLS coefficients derived from C1= GRID probe analysis using the 15 compounds of the thumb training set (contour levels: 0.0008 red, -0.0008 blue). To aid in interpretation, only the highest active (6 in cyan) and one of the lowest active (11 in orange) compounds are shown. Hydrogen atoms are omitted for the sake of clarity.

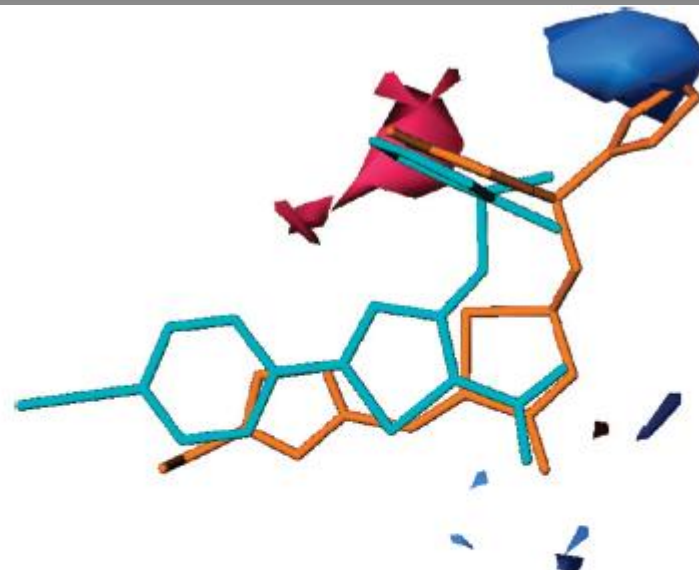


Figure 4. Contour maps of the PLS coefficients derived from OH GRID probe using the 15 compounds of the thumb training set (contour levels: 0.0008 red, -0.0008 blue). To aid in interpretation, only the highest active (6 in cyan) and one of the lowest active (11 in orange) compounds are shown. Hydrogen atoms are omitted for the sake of clarity.

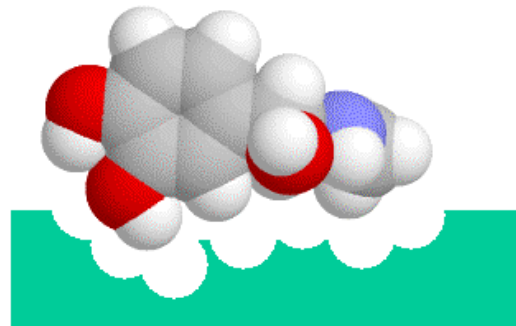
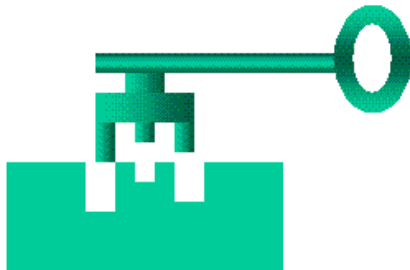
Ricognizione molecolare:

Insieme di interazioni tra molecole e macromolecole

Modello “*Lock and key*”

La proteina ha una sua conformazione all'interno del quale il ligando “fitta” perfettamente.

Emil Fischer(1890).



Modello del *fitting* indotto

Il sito attivo della macromolecola può essere modificato a seconda di come interagisce il ligando.

Daniel Koshland 1958.



- Natura delle interazioni?
- Intensità della ricognizione molecolare?

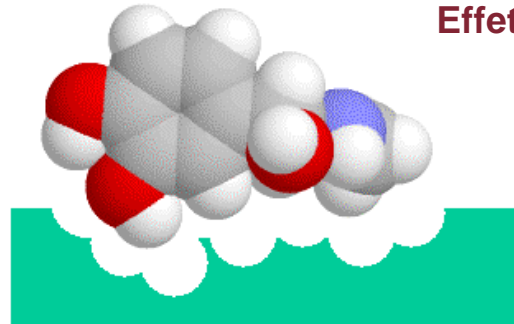
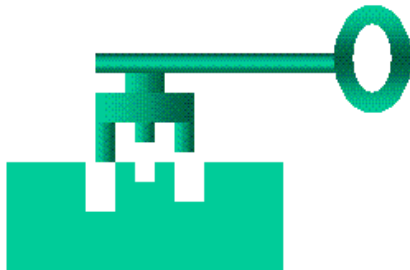
Ricognizione molecolare

La complementarità molecolare altamente specifica tra key (ligando) e lock (recettore) gioca un ruolo chiave nei processi biologici.

La capacità del recettore di agganciarsi al suo ligando con alta specificità e affinità è dovuta alla formazione di una serie di legami deboli e interazioni favorevoli.

Interazioni specifiche ligando-recettore:

- Interazioni elettrostatiche (Non-Cov)
- Forze di van der Waals (Non-Cov)
- Interazioni $\pi - \pi$
- Coordinazione con Metalli
- Interazioni idrofobiche
- Effetti elettromagnetici

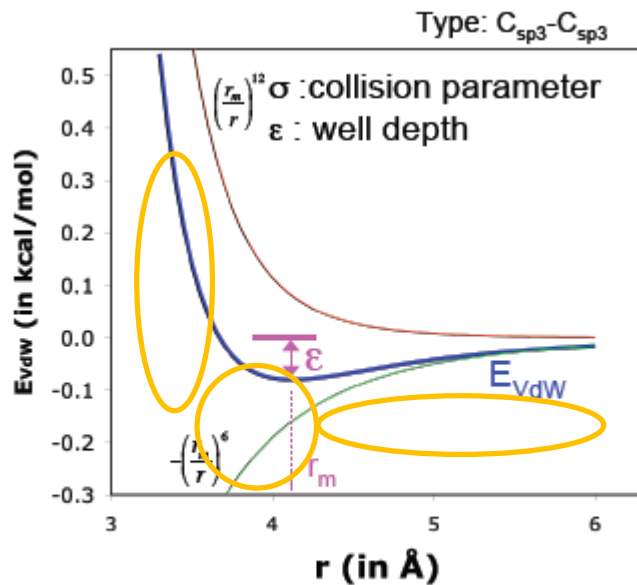


**COMPLEMENTARITA'
MOLECOLARE**

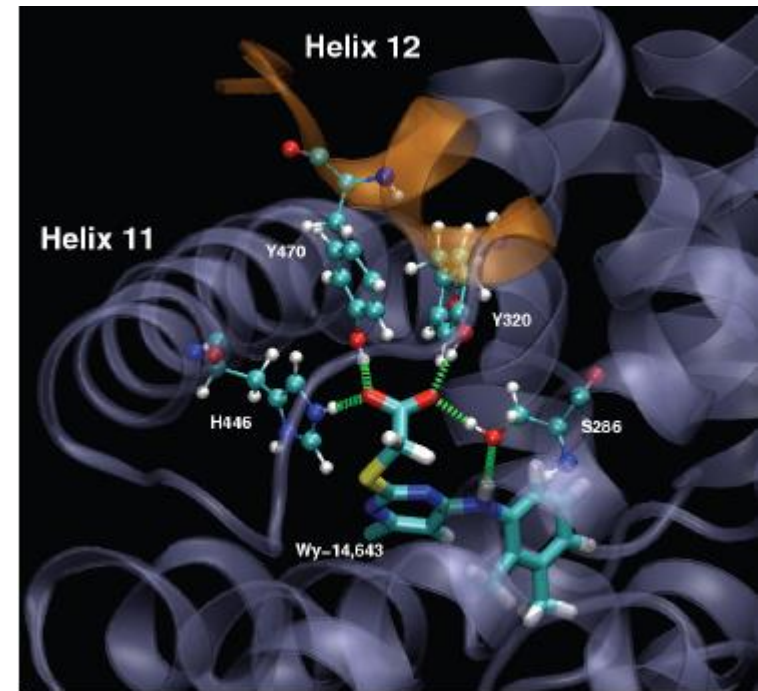
Forze di van der Waals

Debole attrazione intermolecolare causata da dipoli molecolari indotti.

$$E_{\text{vdW}} = \epsilon \left[\left(\frac{r_m}{r} \right)^{12} - 2 \left(\frac{r_m}{r} \right)^6 \right]$$



Repulsive : Pauli exclusion principle
Attractive: induced dipole / induced dipole



Es. Interazione tra il ligando Wy-14,643 e il sito attivo della $\text{PPAR}\alpha$

Quando una molecola di ossigeno si avvicina ad una molecola di acqua orientata verso di essa con l'atomo di ossigeno, la frazione di carica negativa presente su quest'ultimo respinge la nuvola elettronica della molecola di ossigeno e attira la carica positiva nucleare. Si determina uno spostamento del baricentro della carica negativa rispetto a quello della carica positiva nella molecola di ossigeno e quindi induce una polarita'.

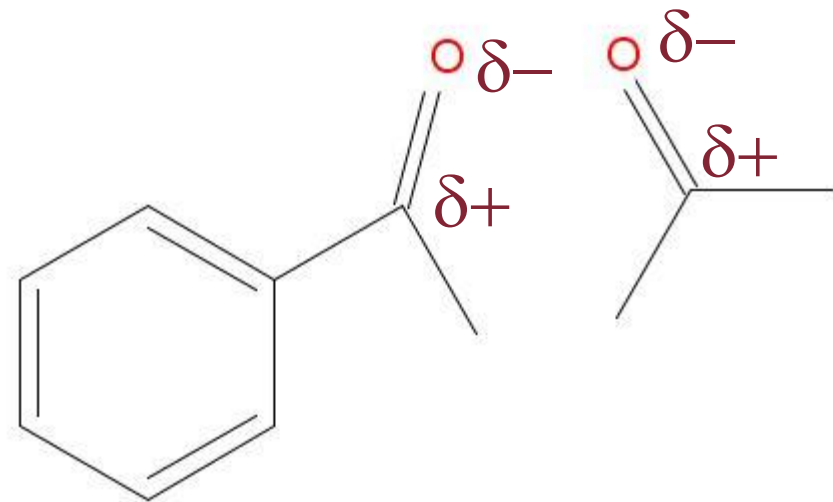
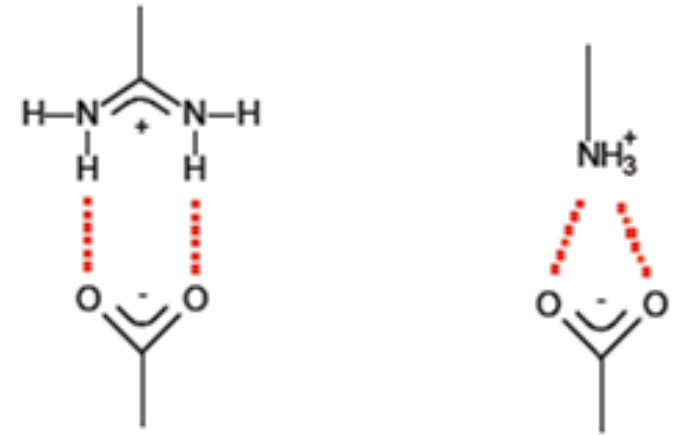
Interazioni Elettrostatiche

La legge di Coulomb

In un mezzo isolante diverso dall'aria la forza F , a parità di cariche e di distanza, risulta generalmente minore. La forza di Coulomb si scrive allora:

$$\vec{F} = \frac{1}{4\pi \cdot \epsilon_0 \cdot \epsilon_r} \cdot \frac{q_1 \cdot q_2}{r^2} \cdot \hat{r}$$

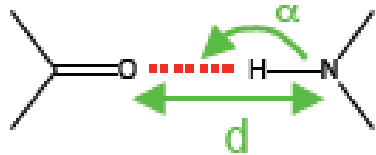
dove ϵ_r è un numero che prende il nome di costante dielettrica relativa (permittività elettrica relativa). Il prodotto $\epsilon_r \times \epsilon_0$ si indica con ϵ , e si chiama costante dielettrica del mezzo (permittività del mezzo).



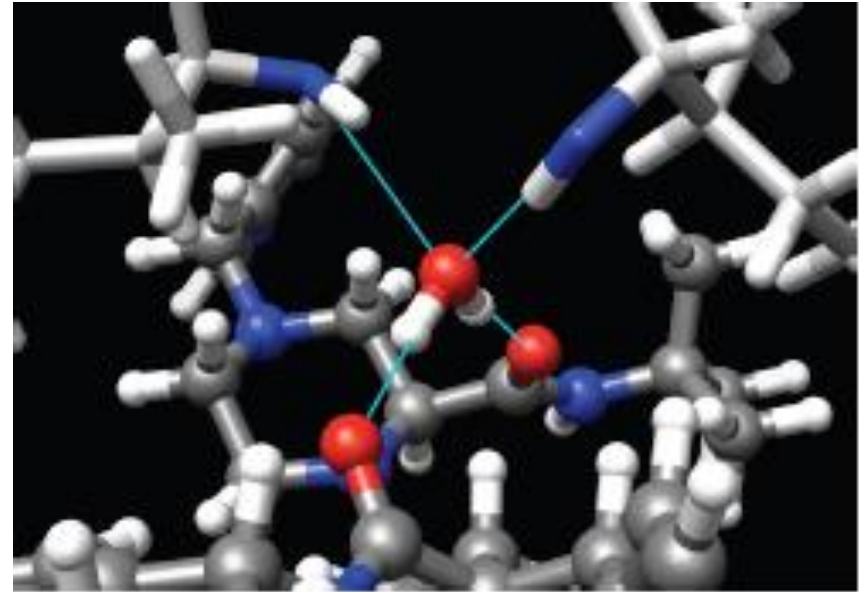
Interazioni Elettrostatiche

Il legame Idrogeno

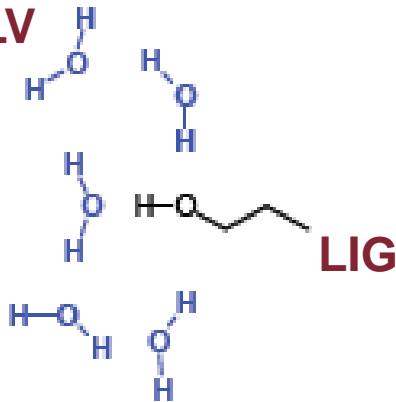
ElegH (solv) – ElegH (comp)
determina se i legami-H
contribuiscono o no all'affinità



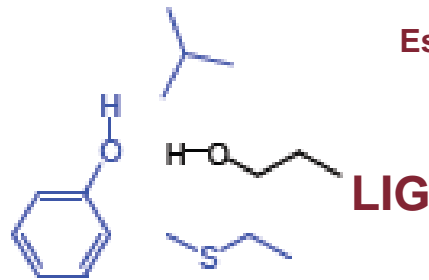
$$d = 2.5 - 3.2 \text{ \AA}$$
$$\alpha = 130 - 180^\circ$$



SOLV



solvent



**REC
complex**

Es. Legame-H tra l'Indinavir, una molecola d'acqua e la Ile50 della proteasi dell'HIV-1 (1HSG in PDB)

Il fattore entropico ed entalpico nel binding



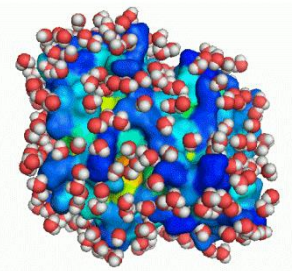
La formazione di un complesso è guidata dal cambiamento di **ENTALPIA** ed **ENTROPIA** del **sistema**

L'equazione fondamentale è:

$$\Delta G = \Delta H - T\Delta S$$

dove ΔG = variazione energia libera, ΔH = variazione entalpia, ΔS = variazione entropia, T = temperatura (K)

Effetti di solvatazione (Termine Entropico + Entalpico)



- La ricognizione molecolare tra due molecole avviene in ambiente acquoso
- Le molecole di acqua mediano l'interazione attraverso ponti idrogeno
- Rottura e formazione di legami-H
- La desolvatazione del ligando e della proteina attraverso la complessazione è:

Sfavorevole (Zone Elettrostatiche)

- Carica del solvente
- Screening delle interazioni elettrostatiche sulla superficie della macromolecola

Favorevole (zone apolari)

- Cavità nel sito attivo
- Riorganizzazione delle molecole d'acqua
- Interazioni di tipo van der Waals tra solvente e ligando
- Gli effetti di desolvatazione sono proporzionali all'area superficiale accessibile

Il fattore entropico nel binding

$$\Delta G_{\text{binding,solution}} = \Delta G_{\text{binding,vacuo}} + \Delta G_{\text{solvation(EI)}} - \Delta G_{\text{solvation(E+I)}}$$

La stabilità di un complesso può essere valutata determinando la costante di equilibrio, che è correlata alla variazione di energia libera:

$$\Delta G = \Delta G_0 - RT \ln K_d$$

dove ΔG_0 =variazione dell'energia libera in condizioni standard, R= costante dei gas, T=temperatura assoluta, K_d = costante di legame espressa come costante di dissociazione con

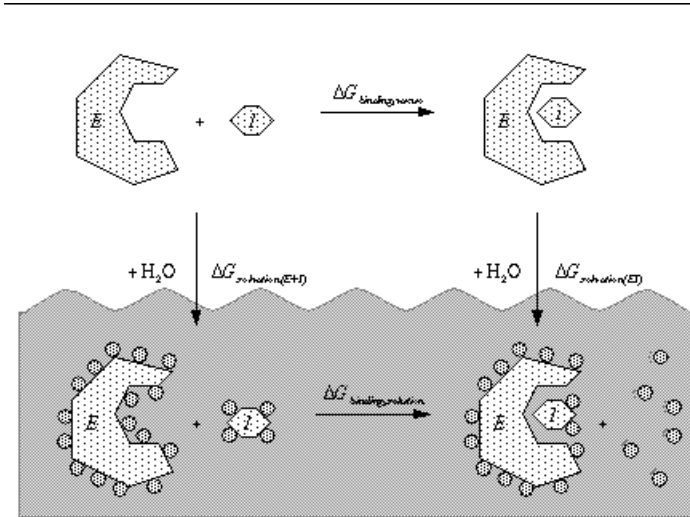


reazione di formazione del complesso è:

$$K_d = [R] [L] / [RL]$$

K_d è definita come la concentrazione del ligando per la quale il 50% dei siti del recettore sono occupati.

L'**effetto idrofobico** è il termine maggiormente stabilizzante per i complessi biomolecolari, mentre le **interazioni coulombiane** e i **legami idrogeno** forniscono specificità alle interazioni proteina-ligando.



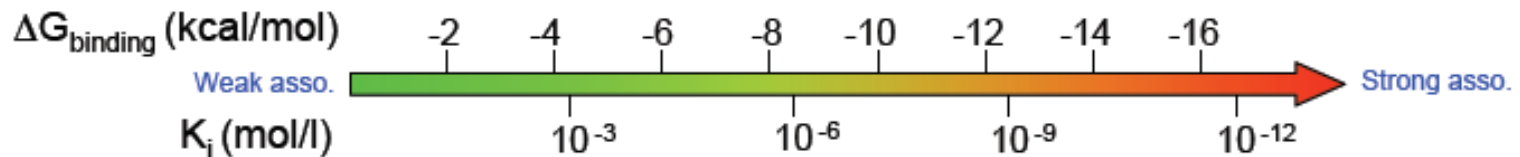
Il fattore entropico nel binding

Binding, dissociation and inhibition constants.
Binding free energy

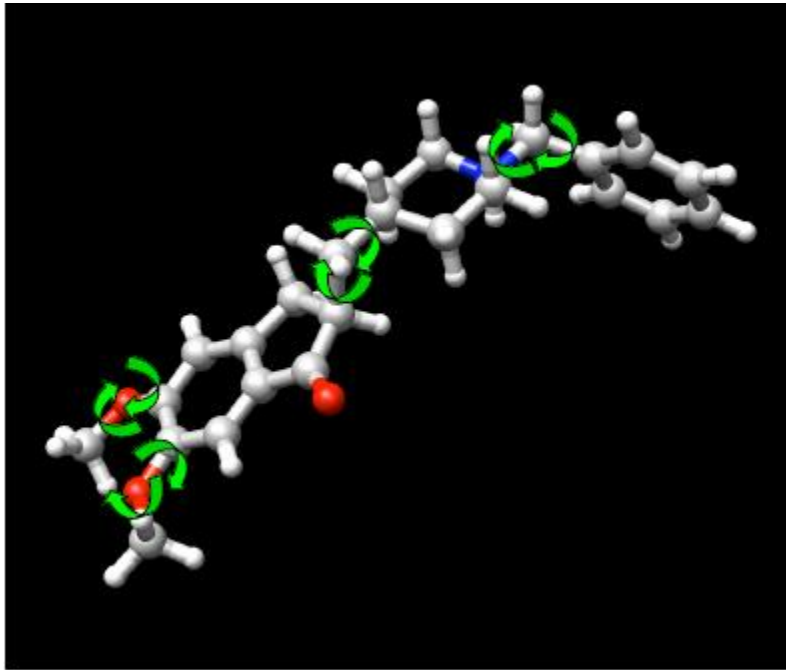


K_b : binding constant, K_d : dissociation constant, K_i : inhibition constant

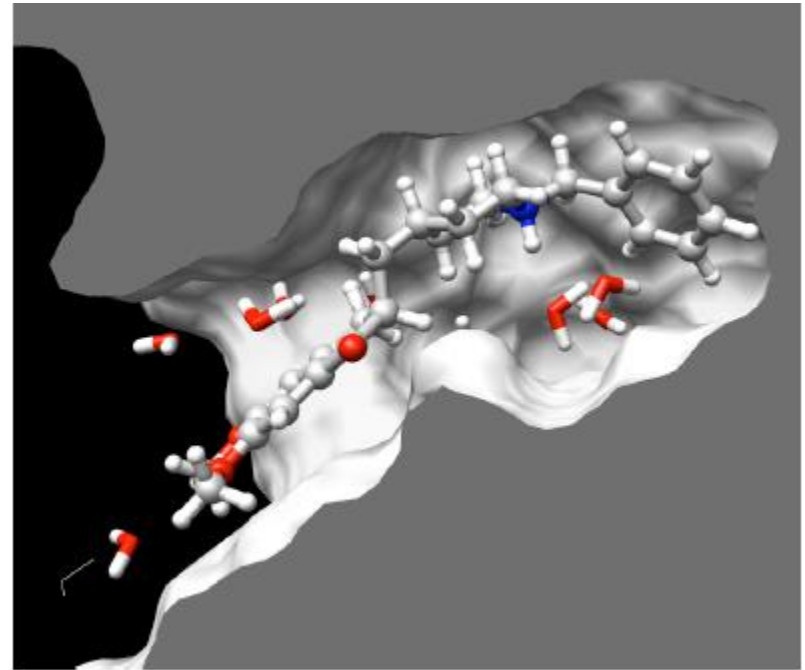
$$\Delta G_{\text{binding}} = -RT \ln K_b = RT \ln K_i = \Delta H - T\Delta S$$



Il fattore entropico nel binding



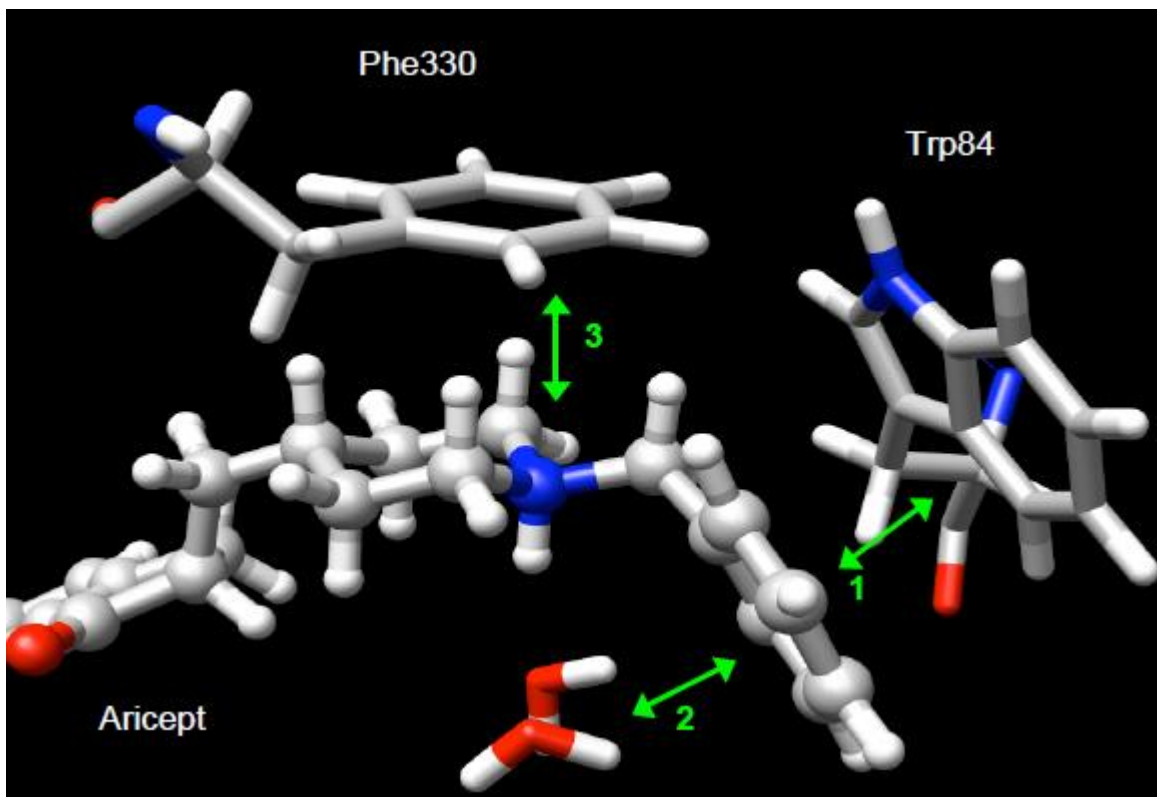
Es. Aricept in soluzione



Es. Aricept nel sito attivo
della acetilcolinesterasi

I gradi di libertà “congelati” durante la complessazione rendono il ligando sfavorito al *binding*

Interazioni π

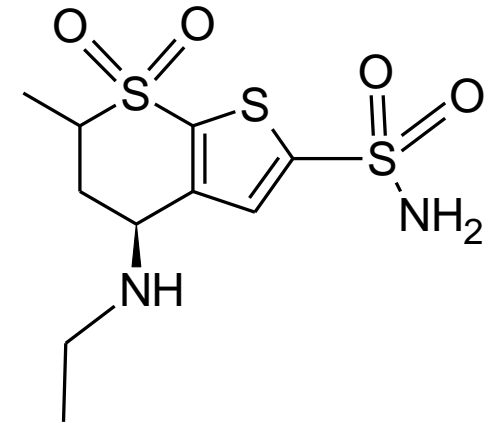
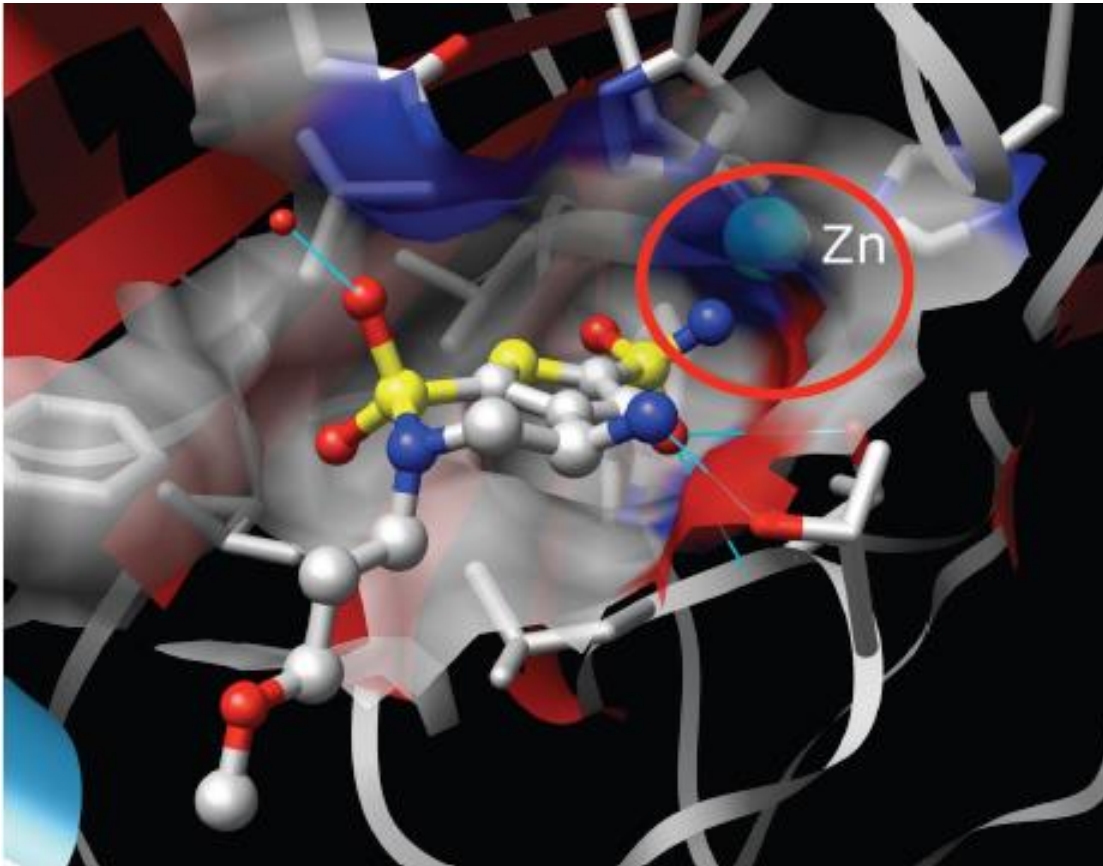


1. Interazioni π - π
2. Interazioni OH- π
3. Interazioni cationi- π

Es. Interazioni π tra l'Aricept (farmaco anti-Alzheimer approvato dalla FDA) e l'acetilcolinesterasi

Coordinazione con Metalli

Legame covalente di coordinazione



Dorzolamide: Inibitore dell'anidasi carbonica, approvato dalla FDA come agente anti-glucoma

DOCKING: Le *Scoring Functions*

Structure-based

With 3D structure for the targeted macromolecule

- Physical based scoring functions :
 - Free energy simulations (FEP, TI)
 - MM-PBSA, MM-GBSA
 - Linear interaction energy (LIE)
- Empirical-based scoring function (regression-based approaches)
Ex: Ludi score
- Knowledge-based approaches (Potentials of Mean Force, PMF)
Ex: PMF score

Utility?

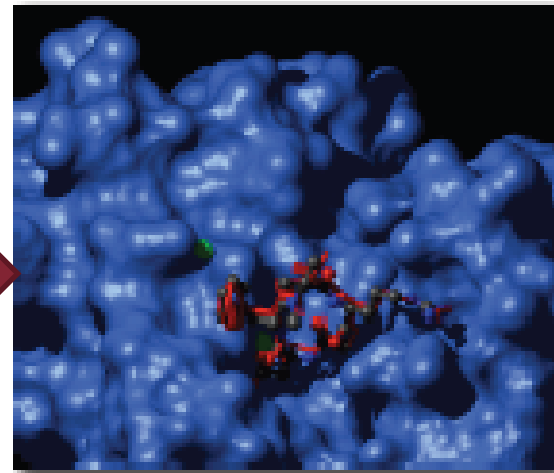
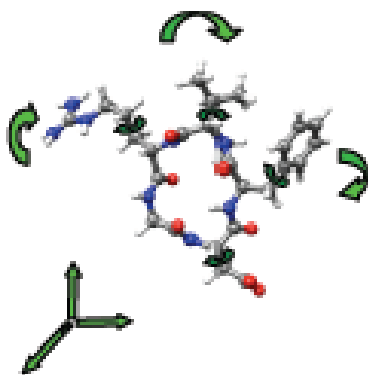
- *Virtual Screening*
- *De novo design*
- *Lead optimization*

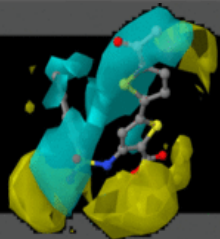
Ligand Docking

Posa o **Binding Mode**: posizione, orientamento e conformazione di un ligando sulla superficie di macromolecole biologiche

Binding Mode sperimentale: Estratta da dati cristallografici e stimata come la migliore posa in termini di *free binding energy*.

Docking: Metodo computazionale utilizzato per la predizione di un binding mode il più vicino possibile allo sperimentale (<2 Å)





Docking Software

Program	ALGORITHM
AutoDock	Lamarckian GA
DOCK	Shape matching (sphere images)
DOCK (NWU version)	Shape matching (sphere images)
FlexX	Incremental construction
FRED	Shape matching (gaussian functions)
Glide	Descriptor matching/MC
GOLD	GA
Hammerhead	Incremental construction
ICM	MC minimization
LigandFit	Shape matching (moments of inertia)
QXP	MC minimization, tree searching and pruning
SLIDE	Descriptor matching
Surflex Dock	Surface-based molecular similarity



Classifying Docking Algorithms

- **Ligand Conformations**
 - Rigid (i.e. protein-protein in bioinformatics)
 - Fixed Sample (i.e. ligand-protein in medicinal chemistry)
 - Flexible (i.e. molecular dynamic in thermodynamic calcs)
- **Constraints**
 - Residues and Pockets
 - Pharmacophores
- **Charges and Tautomers**
- **Water Molecules**



Water Molecules

- **Essential**
 - **Mediates Binding for all Ligands**
- **Optional**
 - **Presence Required by Some Ligands**
 - **Inhibits Binding of Other Ligands**
- **Solvation & Desolvation Free Energy Critical for Scoring Function**

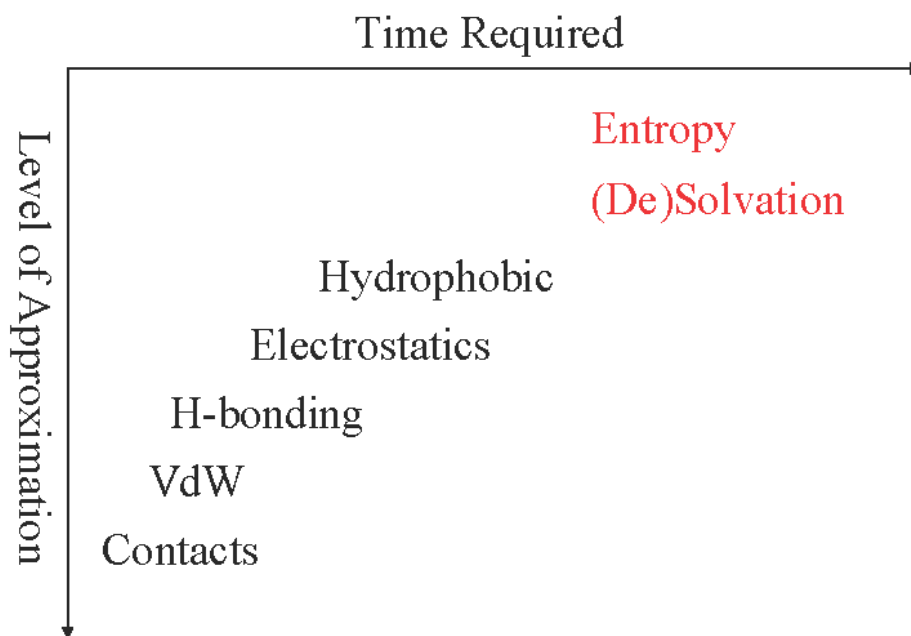


Limitation for Current Methods

- Rigid Proteins Side-Chains
- Binding Relevance for Biological Activity
- Scoring Functions



Terms in Scoring Functions





Classifying Scoring Functions

- Knowledge Based (Atoms Pairs in Contact)
 - DrugScore, PMF
- Energy
 - GOLD, DOCK, LigandFit, MOE
- Energy + Parametrized Solvations
 - Chemscore (Glide, THINK)
- Free Energy Perturbation



Knowledge-Based Functions

$$\text{Score} = \sum_{r < \text{cutoff}} A_{ij}(r)$$

- Potentials of Mean Force (PMF)
 - J Med Chem (1999) 42 p791-804
- DrugScore
 - J Med Chem (2005) 48 p6296-6303
- Less Confused by Crystal Structure Precision





Energy

- Lennard Jones

$$\sum_{ij} (A / r_{ij}^{12} - B/r_{ij}^6)$$

- Torsion Term

$$\Sigma (1 - \cos 2\omega) \text{ Conjugated}$$

$$\Sigma (1 + \cos 3\omega) \text{ Non-conjugated}$$

- Electrostatics

$$\sum_{ij} q_i q_j / \epsilon r_{ij}$$





Enhanced ChemScore

$$\Delta G = \Delta G_0 + \Delta G_{\text{hbond}} * N_{\text{hbond}} + \Delta G_{\text{lipo}} * N_{\text{lipo}} + \Delta G_{\text{bad}} * N_{\text{bad}} + \Delta G_{\text{rot}} * N_{\text{rot}} + E$$

where

ΔG_0 , ΔG_{hbond} , ΔG_{lipo} , ΔG_{bad} , ΔG_{rot} are constants
(-5.48; -3.34; -0.117; 0.058; 2.56)

N_{hbond} is the number of interactions (using geometric criteria)

N_{lipo} is the number of lipophilic contacts (cf PMF, DrugScore)

N_{bad} is the number of lipophilic-hydrophilic contacts (extension)

N_{rot} is the number of frozen rotatable bonds in the ligand

E is the VdW interaction energy and ligand torsional energy
(extension)





Free Energy Perturbation

$$\Delta G_{\text{sol}} = - \Delta G_{\text{sol}}(\text{ligand}) - \Delta G_{\text{sol}}(\text{protein}) \\ + \Delta G_{\text{gas}} + \Delta G_{\text{sol}}(\text{complex})$$

- Error Prone due to Subtraction of Large Numbers
- Solvent Accessible Surface Area (SASA) approximation (cf ChemScore)
- J Med Chem (2004) 47 p3065-74





Validation and Results

- Reproduce Ligand-Protein Crystal Structures
 - RMS Deviation of non-H Atoms
 - Docking Score
- Dock Actives
 - Used for Developing Scoring Functions
- Prediction
 - Enrichment over Random
 - Percentage of False Positives





SBDD

What We Can and Cannot Do

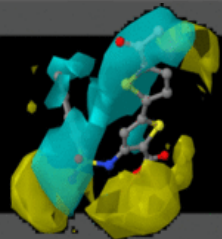
- **Routine**
 - Small molecule conformation generation and energy profiling
 - Visualizing crystal structures
 - Binding site characterization
 - Virtual screening to enrich databases for actives
 - Cheminformatics, ligand-based, and structure-based
 - Predict binding modes when receptor can be treated rigidly
- **Difficult**
 - Separating highly from weakly active compounds
 - Predicting side chain rearrangements and backbone relaxation
- **Very Challenging**
 - Predicting binding free energies
 - Predicting large scale protein movements
 - Mapping free energy surfaces
 - Understanding off-target effects
 - Other ADME-Tox



Comparative binding energy analysis for binding affinity and target selectivity prediction

Stefan Henrich,¹ Isabella Feierberg,² Ting Wang,¹ Niklas Blomberg,² and Rebecca C. Wade^{1*}

Proteins: Structure, Function, and Bioinformatics, 2010, 78, 135–153



COMBINER COMBINE with Autogrid/R

rcmd
www.rcmd.it

JOURNAL OF
**CHEMICAL INFORMATION
AND MODELING**

Article

pubs.acs.org/jcim

3-D QSAutogrid/R: An Alternative Procedure To Build 3-D QSAR Models. Methodologies and Applications

Flavio Ballante[†] and Rino Ragno^{*,†}

J Comput Aided Mol Des
DOI 10.1007/s10822-012-9586-6

Comprehensive model of wild-type and mutant HIV-1 reverse transcriptases

Flavio Ballante · Ira Musmuca · Garland R. Marshall ·
Rino Ragno

Journal of
**Medicinal
Chemistry**

Brief Article

pubs.acs.org/jmc

2-(Alkyl/Aryl)Amino-6-Benzylpyrimidin-4(3H)-ones as Inhibitors of Wild-Type and Mutant HIV-1: Enantioselectivity Studies

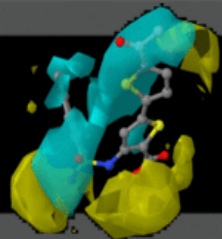
Dante Rotili,^{†,#} Alberta Samuele,^{‡,#} Domenico Tarantino,[†] Rino Ragno,[†] Ira Musmuca,[†] Flavio Ballante,[†] Giorgia Botta,[†] Ludovica Morera,[†] Marco Pierini,[†] Roberto Cirilli,[§] Maxim B. Nawrozkij,^{||} Emmanuel Gonzalez,[⊥] Bonaventura Clotet,[⊥] Marino Artico,[†] José A. Esté,^{*,⊥} Giovanni Maga,^{*,‡} and Antonello Mai^{*,†}

ACS Publications

© 2012 American Chemical Society

3558

dx.doi.org/10.1021/jm201308v | J. Med. Chem. 2012, 55, 3558–3562



COMBINEr

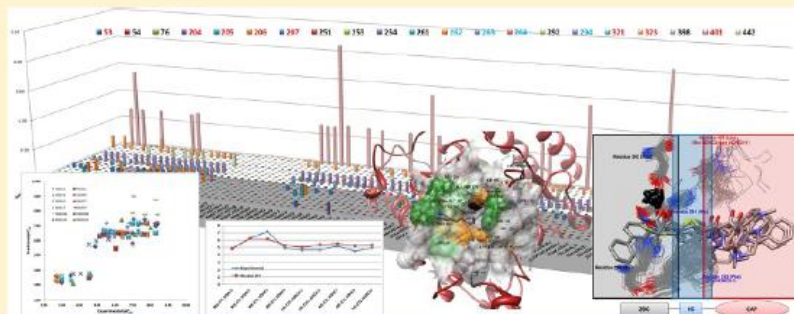
COMBINE with Autogrid/R

Histone Deacetylase Inhibitors: Structure-Based Modeling and Isoform-Selectivity Prediction

Laura Silvestri,[†] Flavio Ballante,[†] Antonello Mai,[‡] Garland R. Marshall,^{†,§} and Rino Ragno^{*,†}

Rome Center for Molecular Design Dipartimento Chimica e Tecnologie del Farmaco, Facoltà di Farmacia e Medicina, [†]Istituto Pasteur—Fondazione Cenci Bolognetti Dipartimento Chimica e Tecnologie del Farmaco, Facoltà di Farmacia e Medicina, Sapienza Università di Roma, Rome, Italy

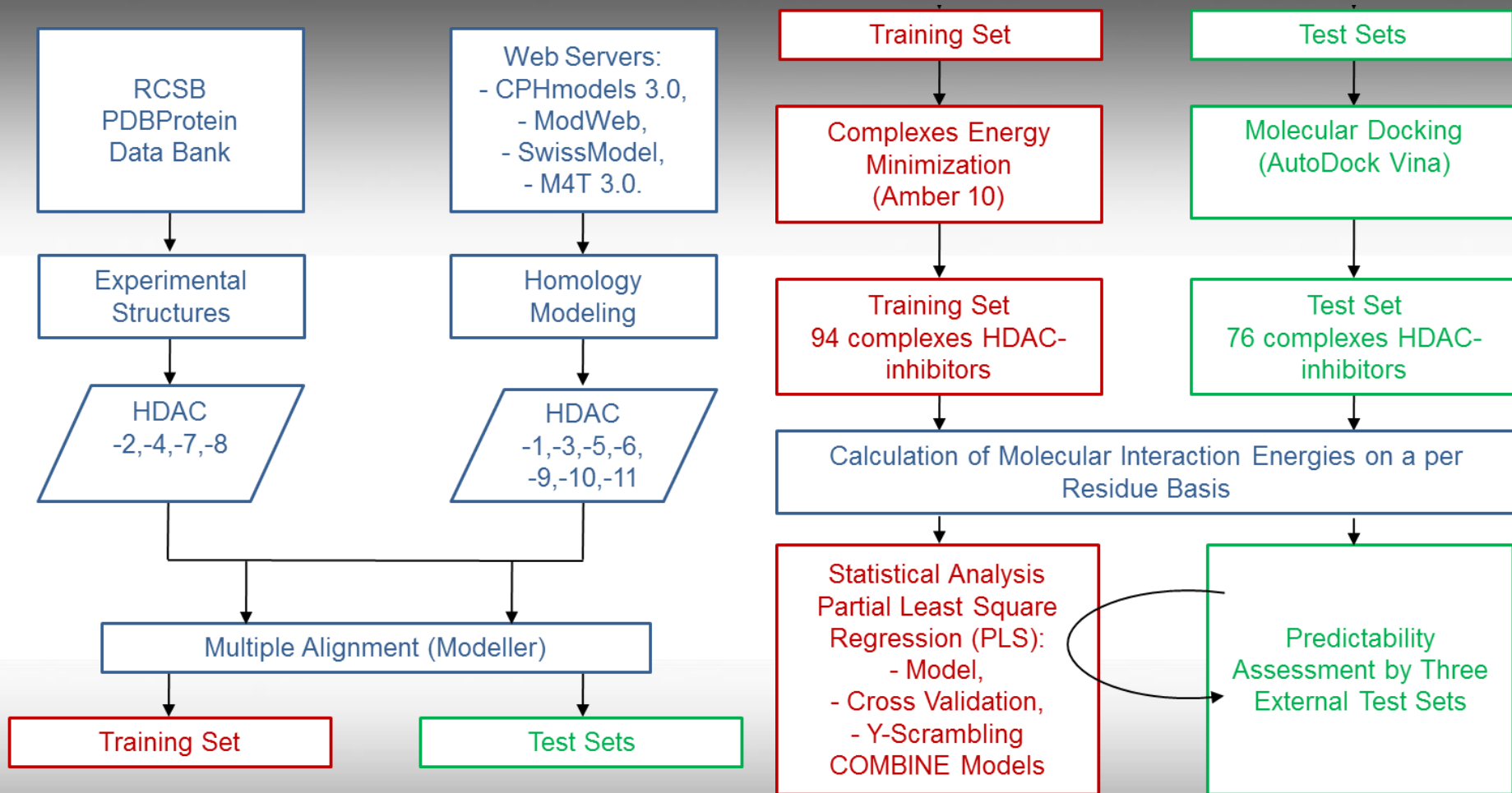
Supporting Information

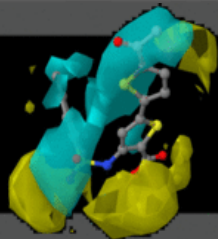


ABSTRACT: An enhanced version of comparative binding energy (COMBINE) analysis, named COMBINEr, based on both ligand-based and structure-based alignments has been used to build several 3-D QSAR models for the eleven human zinc-based histone deacetylases (HDACs). When faced with an abundance of data from diverse structure–activity sources, choosing the best paradigm for an integrative analysis is difficult. A common example from studies on enzyme–inhibitors is the abundance of crystal structures characterized by diverse ligands complexed with different enzyme isoforms. A novel comprehensive tool for data mining on such inhomogeneous set of structure–activity data was developed based on the original approach of Ortiz, Gago, and Wade, and applied to predict HDAC inhibitors’ isoform selectivity. The COMBINEr approach (apart from the AMBER programs) has been developed to use only software freely available to academics.



HDAC/COMBINER Protocol

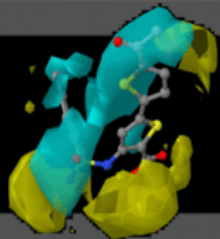




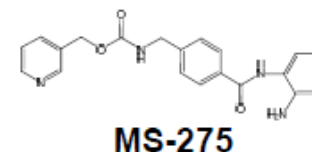
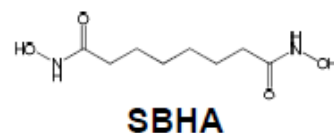
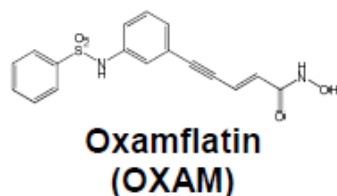
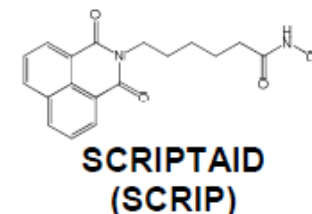
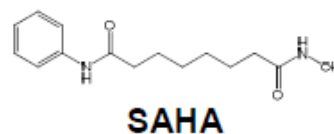
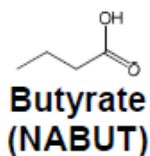
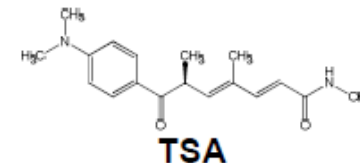
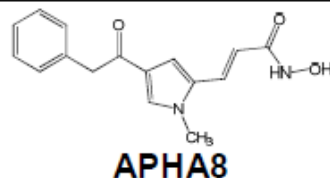
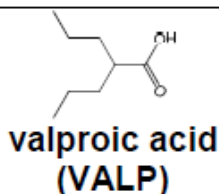
COMBINER Training Set

PDB code (ligand names)	Ligand structure	PDB code (ligand names)	Ligand structure
3MAX (LLX)		1T69 3C0Z (SAHA)	
3F07 (APHA8)		1W22 (NHB)	
1T64 3C10 (TSA)		2VQM (HA3)	
1T67 (MS-344)		2VQJ (TFMK)	

PDB code	HDAC			PDB code	HDAC		
	Class	Number	IC ₅₀ (μM)		Class	Number	IC ₅₀ (μM)
3MAX ¹¹ (LLX)	I	2	0.9	1W22 ¹⁴ (NHB)	I	8	0.175
3F07 ¹² (APHA8)	I	8	2.8	2VQM ¹⁷ (HA3)	II a	4	0.978
1T64 ¹⁴ (TSA)	I	8	1.1	2VQJ ¹⁷ (TFMK)	II a	4	0.367
1T67 ¹⁴ (MS-344)	I	8	0.249	3C0Z ¹⁸ (SAHA)	II a	7	0.05
1T69 ¹⁴	I	8	2.2	3C10 ¹⁸ (TSA)	II a	7	0.014



COMBINER Training Set



HDAC	CLASS	I					IIa			IIb		IV
	Number	1	2	3	8	4	5	7	9	6	10	11
valproic acid (VALP)	1000	1000	226.08	228.85	-	2000	-	2000 ¹⁹	1000	1000	-	
Butyrate (NABUT)	319	28.9	22.5	85.6	30	2000	30	2000 ¹⁹	1000	292	-	
Oxamflatin (OXAM)	0.05	0.2	0.01	2.2	0.03	-	0.03	-	0.09	0.05	-	
APHA8	3.7	7.4	0.42	2.8	3.1	-	3.1	-	0.1	4.2	-	
SAHA	0.1	0.44	0.02	2.2	0.05	0.378	0.05	0.316	0.02	0.1	0.362	
SBHA	2.1	4.6	0.41	3.7	1.4	-	1.3	-	0.1	2.3	-	
TSA	0.005	0.021	0.005	1.1	0.014	0.0165	0.014	0.0381	0.005	0.005	0.0152	
SCRIPTAID (SCRIP)	0.17	0.64	0.03	2.3	0.2	-	0.16	-	0.004	0.17	-	
MS-275	13	0.51	0.07	30	12	-	6.2	-	21	11.5	-	

Life Sciences 82 (2008) 1050–1058

Contents lists available at ScienceDirect

Life Sciences

journal homepage: www.elsevier.com/locate/lifescie

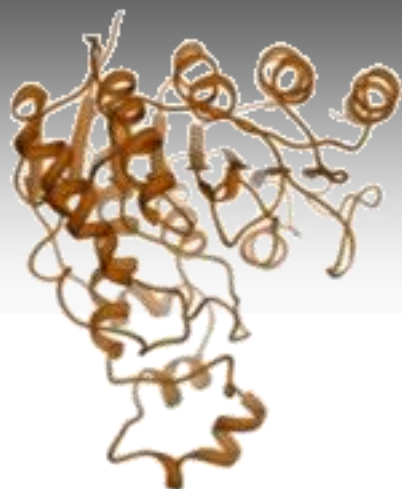


The use of diversity profiling to characterize chemical modulators of the histone deacetylases

Leonard Blackwell, Jacqueline Norris, Carla M. Suto, William P. Janzen *



Experimental Data



HDAC2

HDAC4



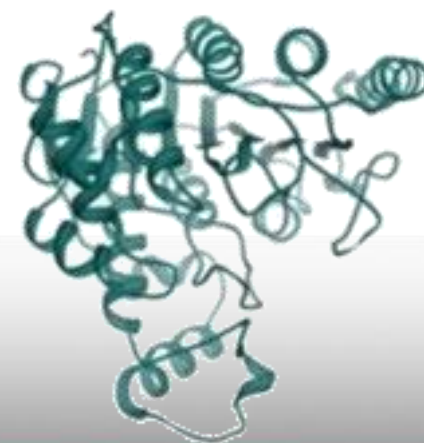
RCSB **PDB**
PROTEIN DATA BANK

Experimental Structures



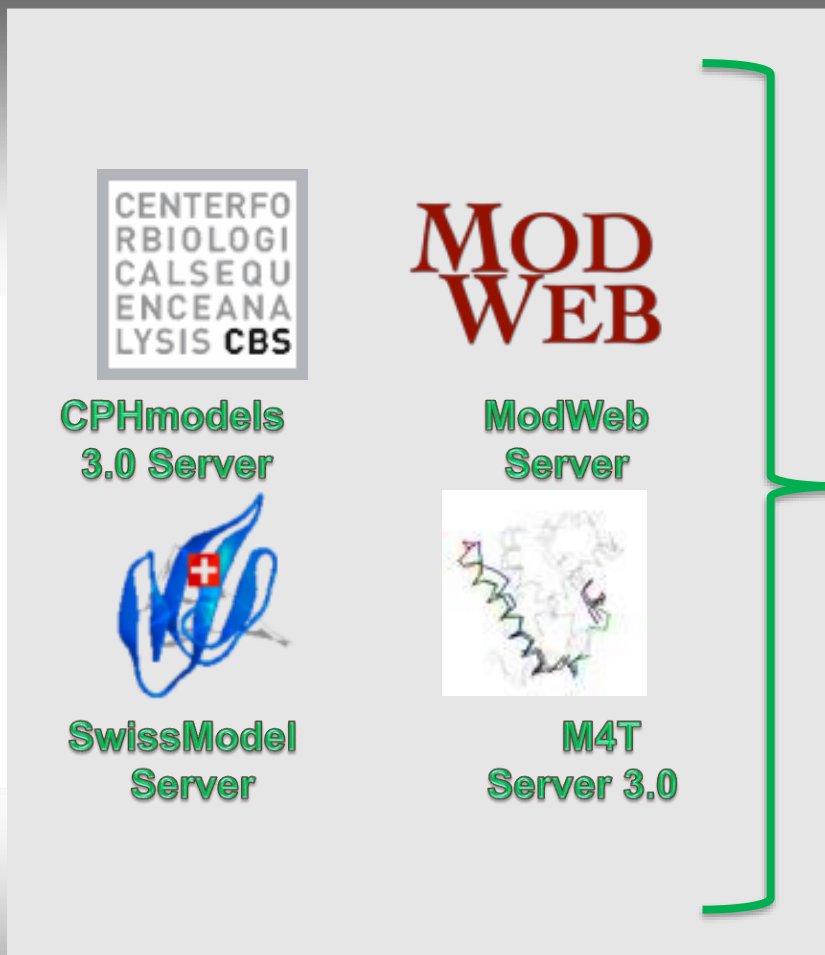
HDAC7

HDAC8





Homology Modeling



4 Homology Models

For Each

HDAC-1,-3,-5,-6A,-6B,-9,-10,-11



Docking Assessment

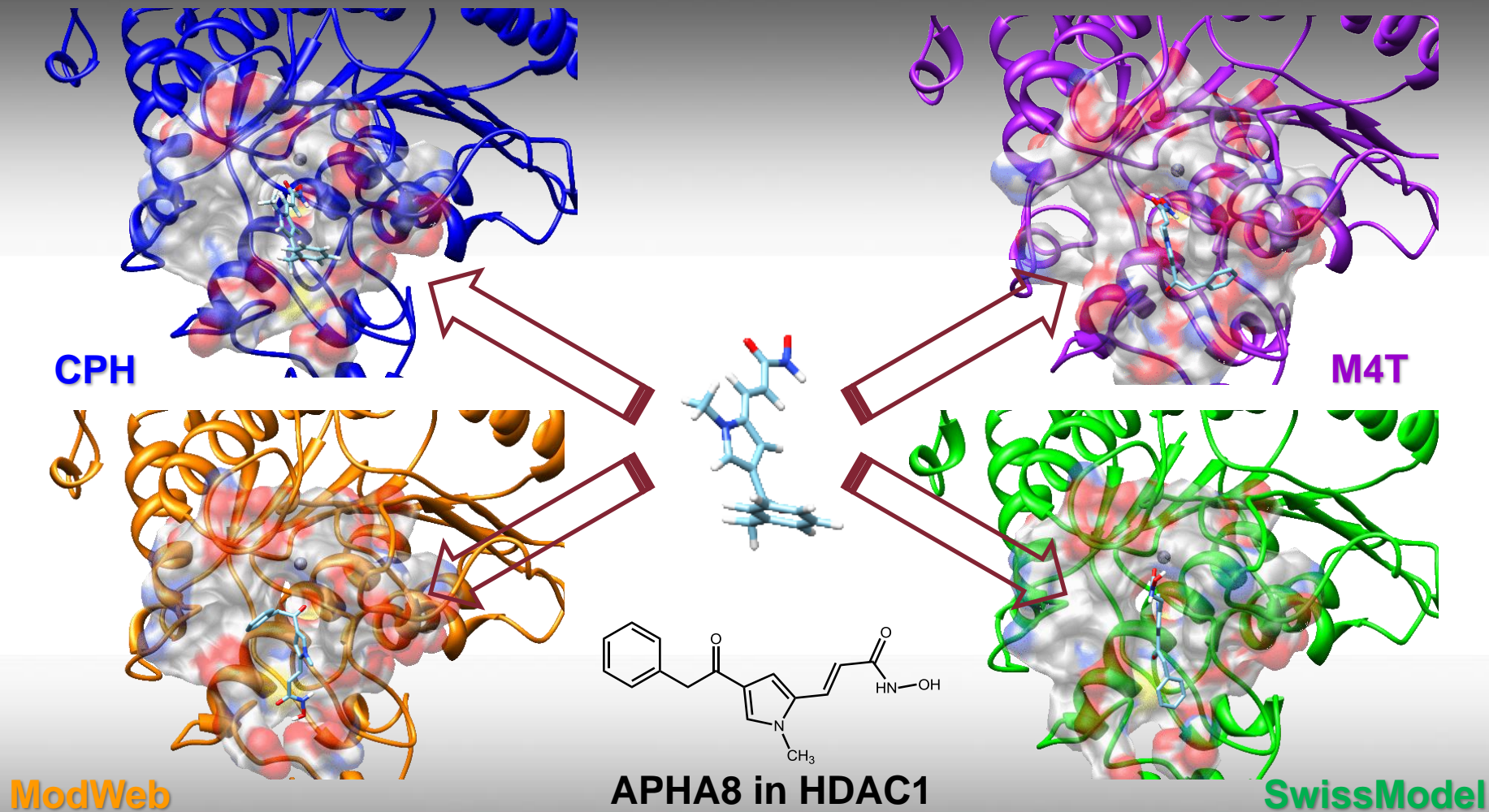
$$DA \text{ (Docking Accuracy)} = f_{RMSD \leq 2} + 0.5 (f_{RMSD \leq 3} - f_{RMSD \leq 2})$$

Redocking results (RMSD) with AutoDockVina

Complex name	Best docked	Best Cluster	Best Fit
LLX.HDAC2	0.24	0.24	0.24
HA3.HDAC4	3.87	2.34	1.93
TMFK.HDAC4	4.02	1.9	1.46
SAHA.HDAC7	2.45	2.45	1.88
TSA.HDAC7	2.19	2.19	1.21
APHA.HDAC8	1.43	1.43	1.43
SAHA.HDAC8	2.49	2.49	1.72
TSA.HDAC8	2.09	1.22	1.22
DA %	50	75	100

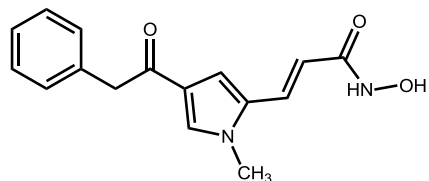


Docking Assessment

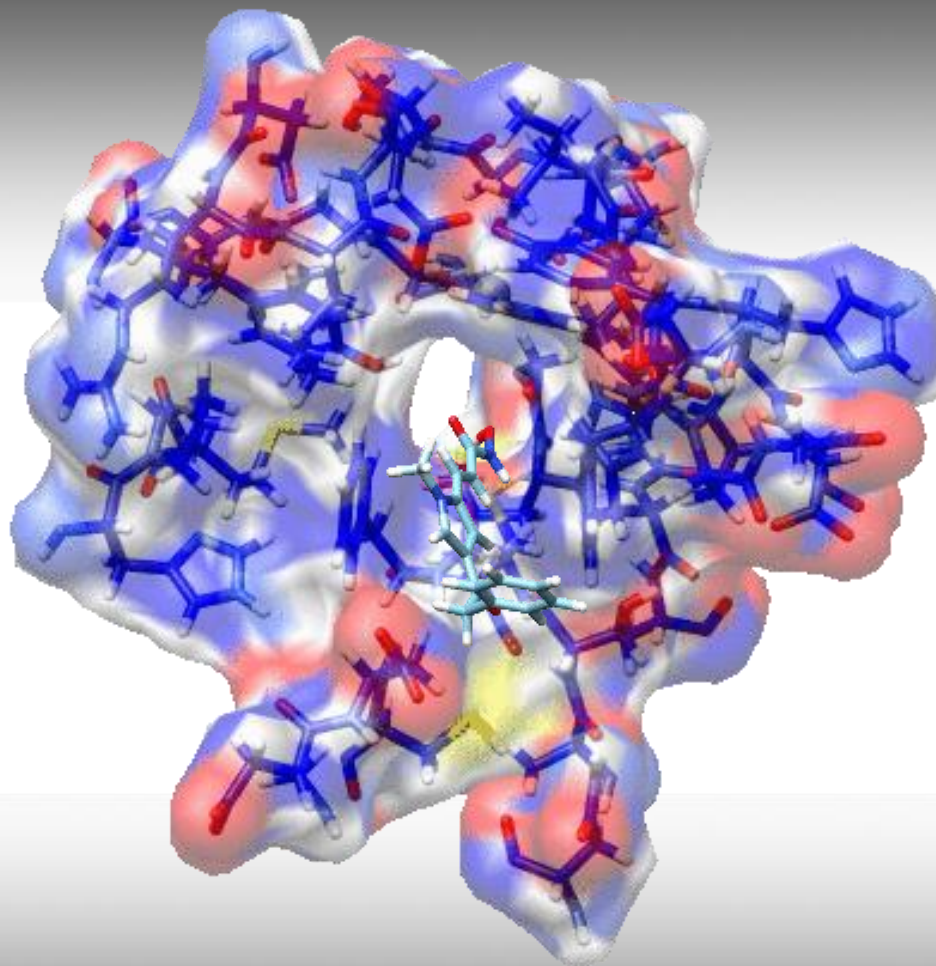




Cross-Docking → Flex-Docking



APHA8 in HDAC1



CPH

ModWeb

M4T

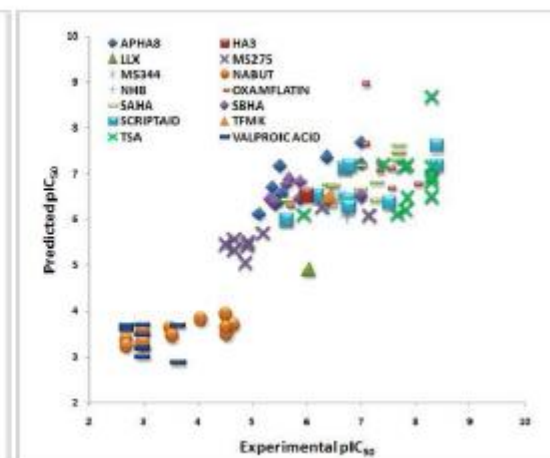
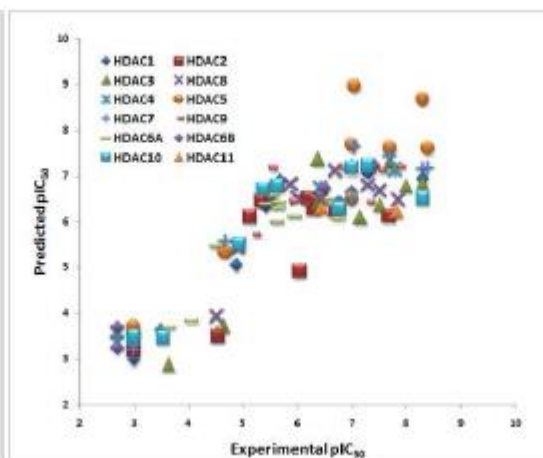
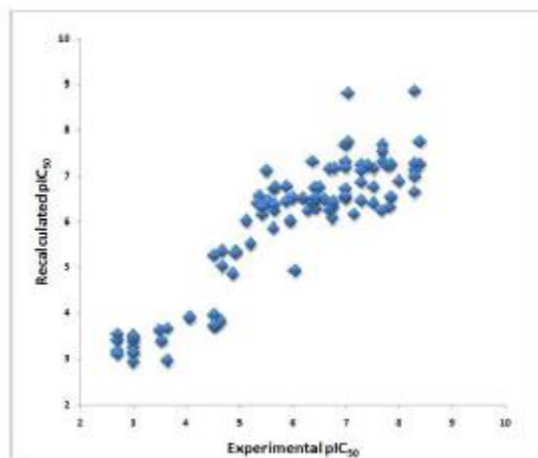
SwissModel



COMBINER Model Building

Statistical results of the COMBINER models.

#	Field	PC	r^2	SDEC ^c	q^2_{K5fold}	SDEP _{R5G-LSO}	q^2_{LOO}	SDEP _{LOO}	scrambled q^2	
									% positive values	Max. value
1	ELE	2	0.69	0.91	0.67	0.94	0.68	0.93	5	0.07
2	STE	2	0.27	1.40	0.14	1.52	0.15	1.51	n.d.	n.d.
3	DRY	2	0.46	1.21	0.34	1.33	0.36	1.32	n.d.	n.d.
4	ELE+STE	2	0.74	0.84	0.68	0.93	0.68	0.93	2	0.05
5	ELE+DRY	2	0.80	0.73	0.76	0.81	0.76	0.81	6	0.08
6	STE+DRY	3	0.54	1.11	0.33	1.34	0.35	1.33	n.d.	n.d.
7	ELE+DRY+STE	2	0.77	0.78	0.72	0.87	0.72	0.87	4	0.04

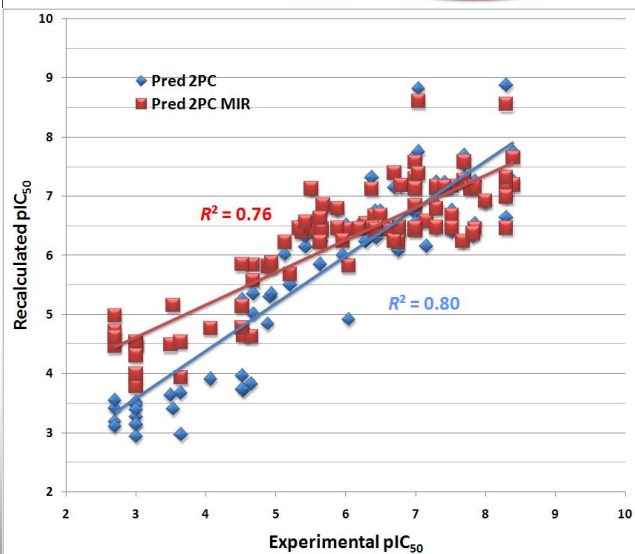
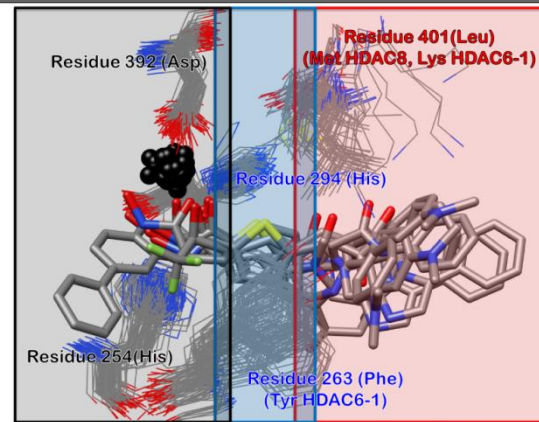
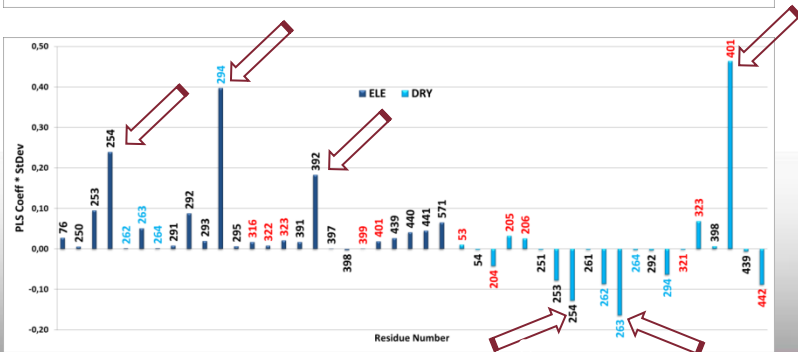
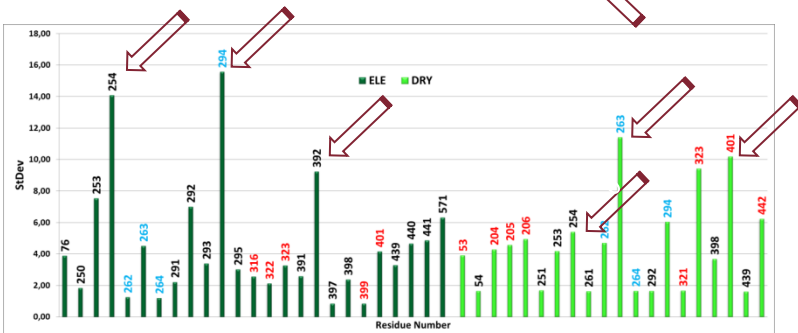
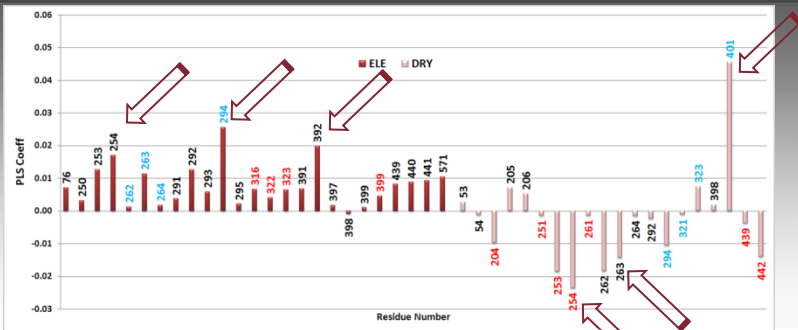


HDAC Inhibitors: Structure-Based Modeling and Isoform-Selectivity Prediction

SB 3-D QSAR



COMBINer Model Interpretation

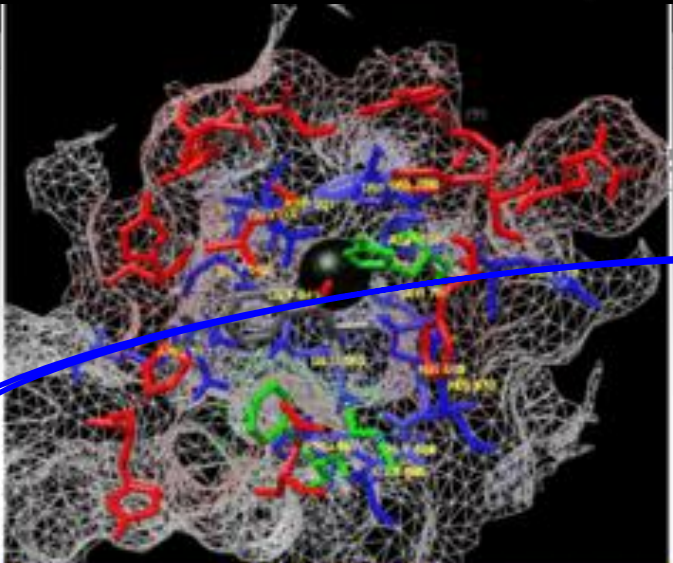
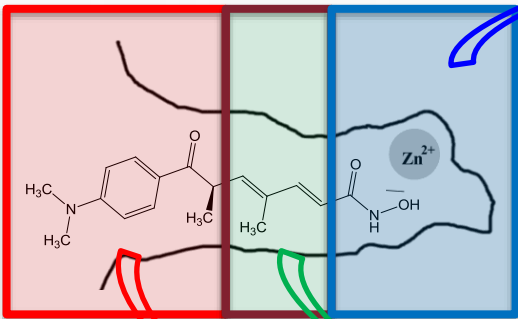


HDAC Inhibitors: Structure-Based Modeling and Isoform-Selectivity Prediction

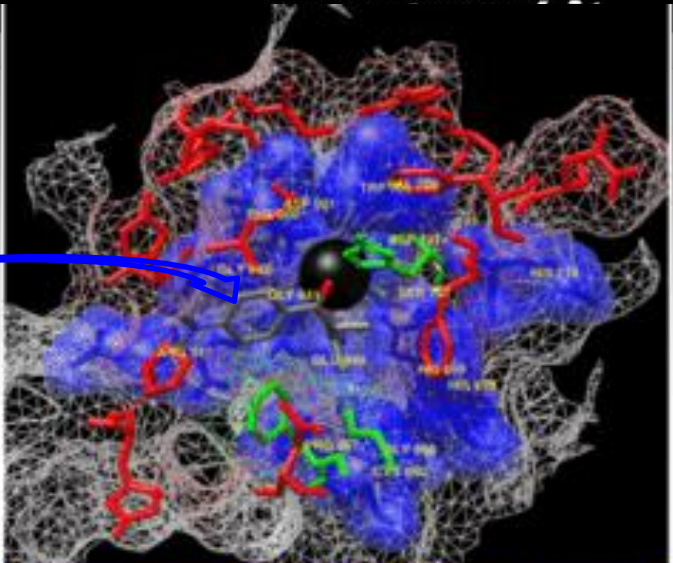
SB 3-D QSAR



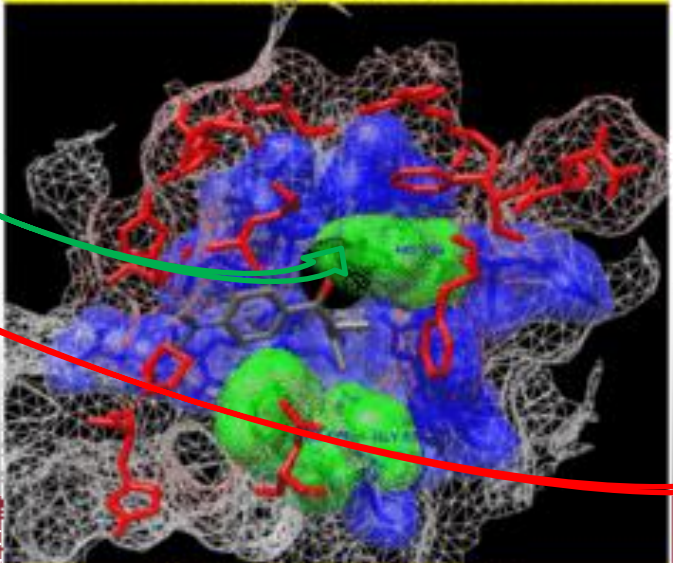
COMBINER Model Interpretation *rcmd*



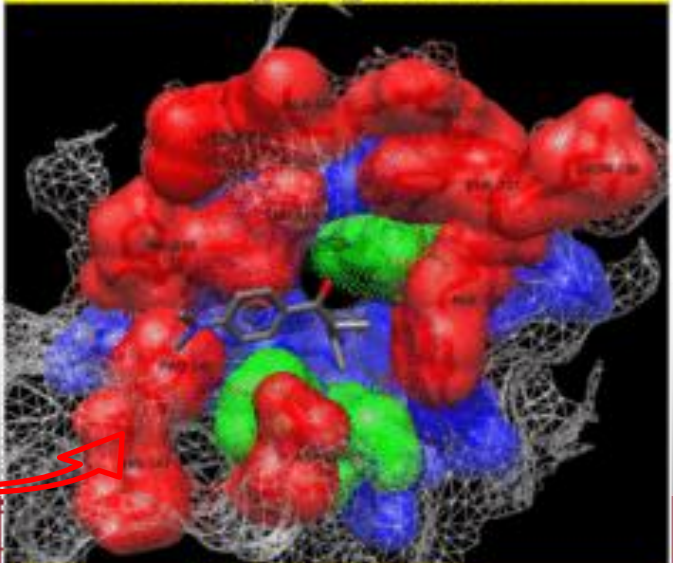
No_Surfaces



BLUE_ZBG_Residues



GREEN_Tube_Residues



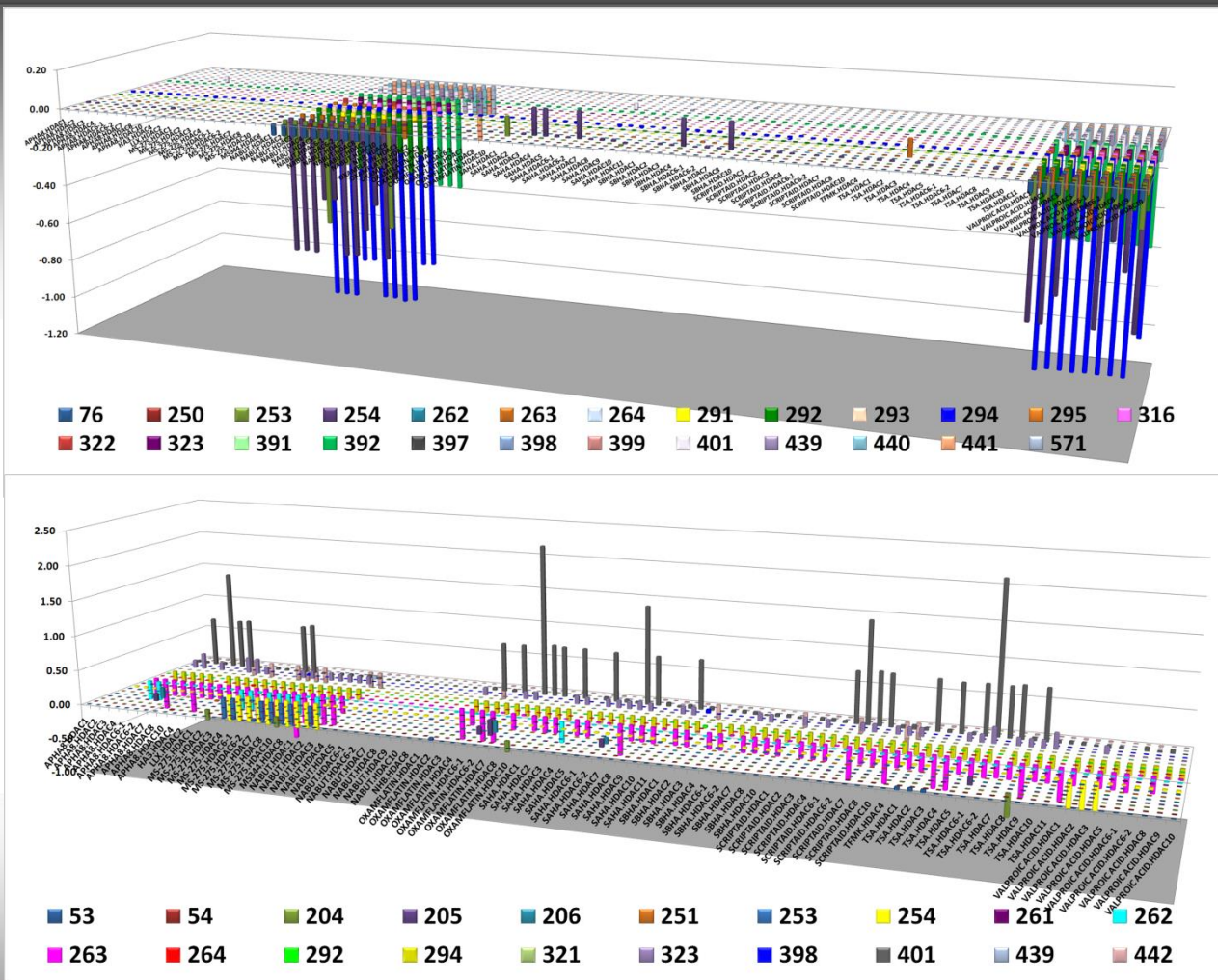
RED_Rim_Residues

TSA.HDAC7

HDAC Inhibitors: St
Isoform-Selectivity f



COMBINEr Model Interpretation

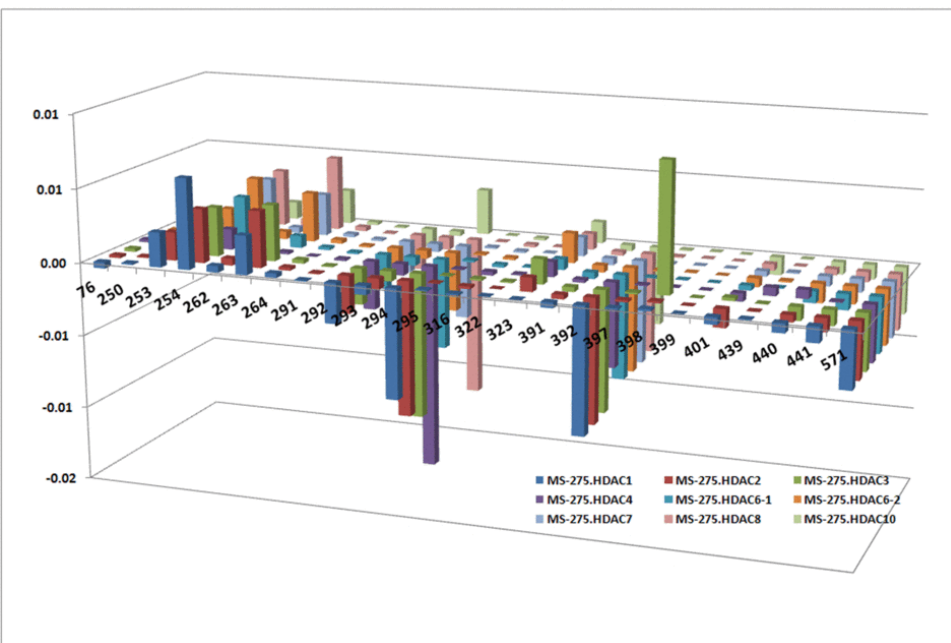


HDAC Inhibitors: Structure-Based Modeling and Isoform-Selectivity Prediction

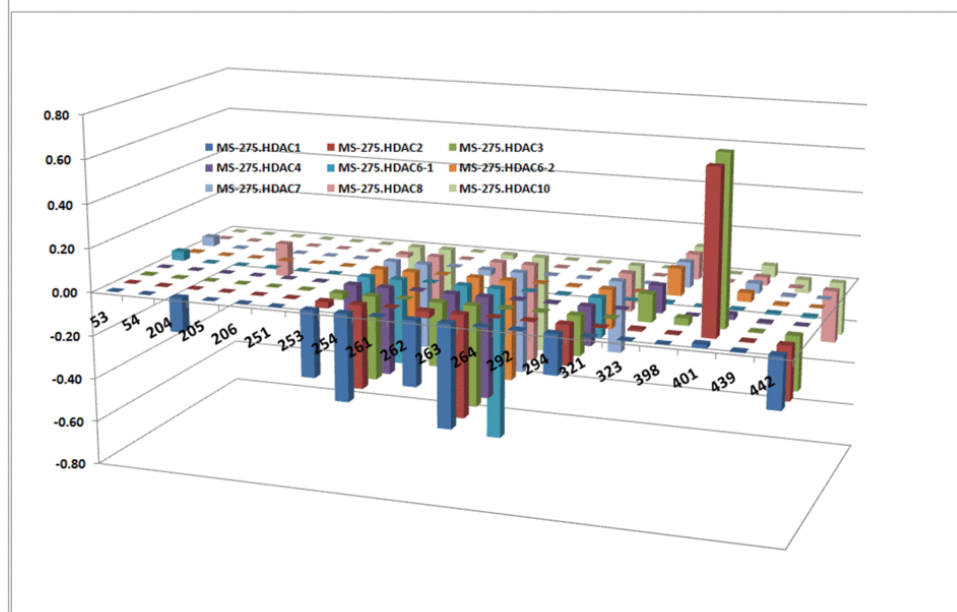
SB 3-D QSAR



Activity Contribution Histograms



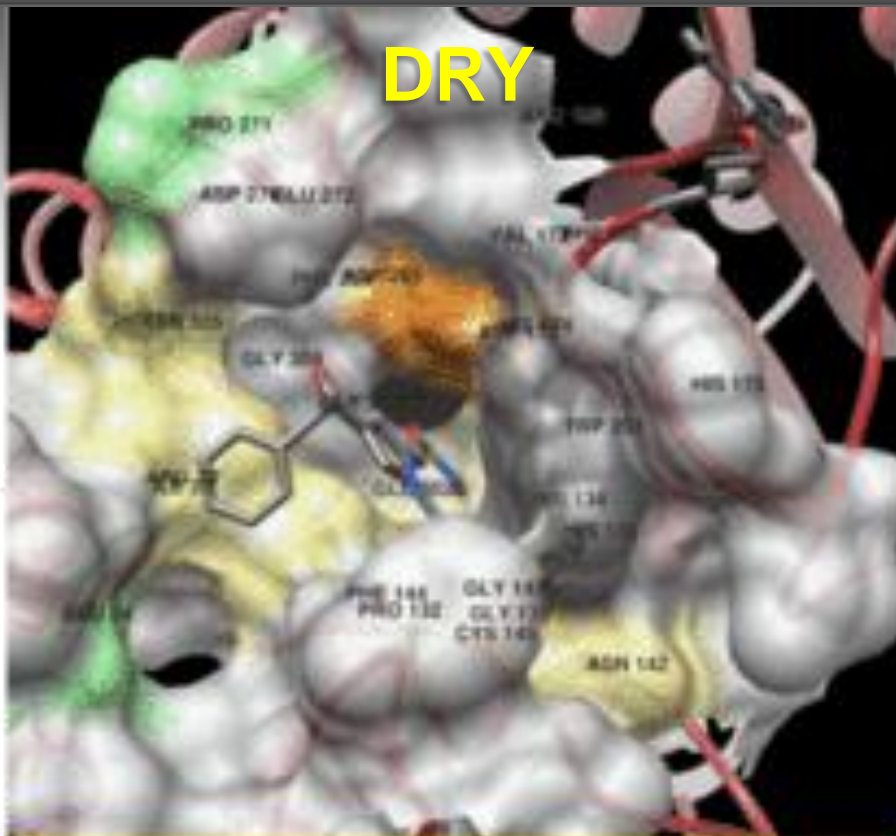
MS275.ELE



MS275.DRY



COMBINER Model Interpretation

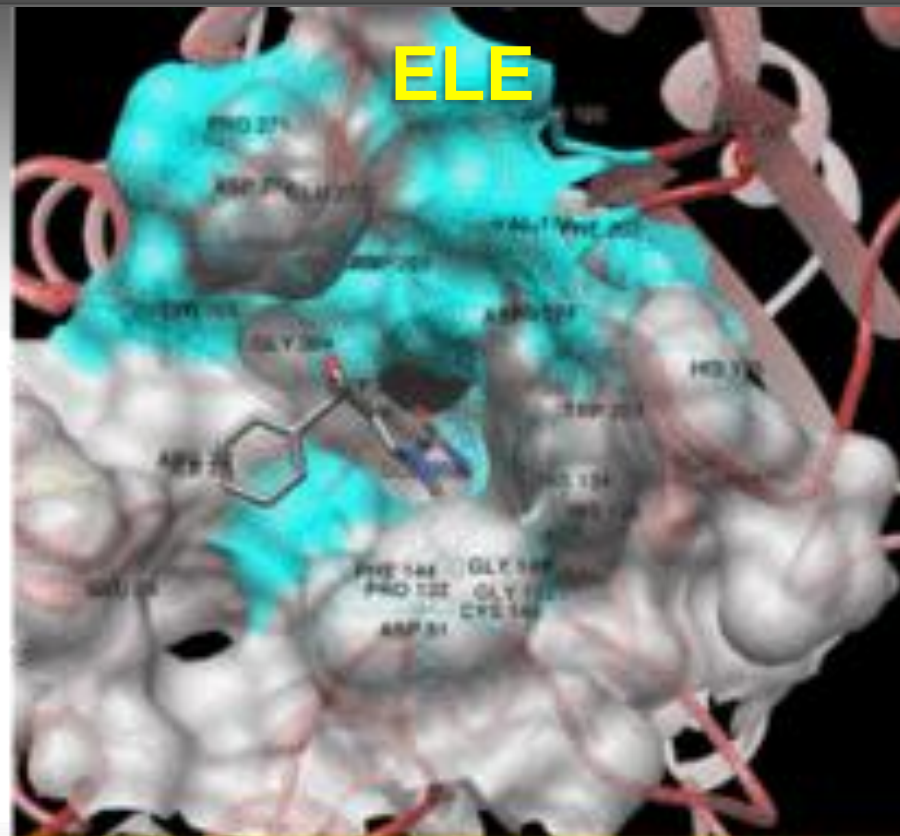


DRY

APHA8.HDAC10.SwissModel.DRY

Decreasing Activity

Increasing Activity



ELE

APHA8.HDAC10.SwissModel.ELE

Decreasing Activity

Increasing Activity



Proteochemometric



Proteochemometric (PCM) modelling is a computational method to model the bioactivity of multiple ligands against multiple related protein targets simultaneously.

PCM modeling can be conceptualized as an extension of QSAR modeling that exploits chemogenomic data by performing a quantitative evaluation of ligand and target structural similarities. As a result, this technique allows the simultaneous navigation, inter- and extrapolation in both chemical space (i.e. ligands) and biological space (i.e. protein target). By the explicit combination of target and ligand information in a single model PCM is capable to analyze and predict SmARs (Structure-multiple Activity Relationships) of a set of compounds.



REVIEW

[View Article Online](#)

[View Journal](#) | [View Issue](#)

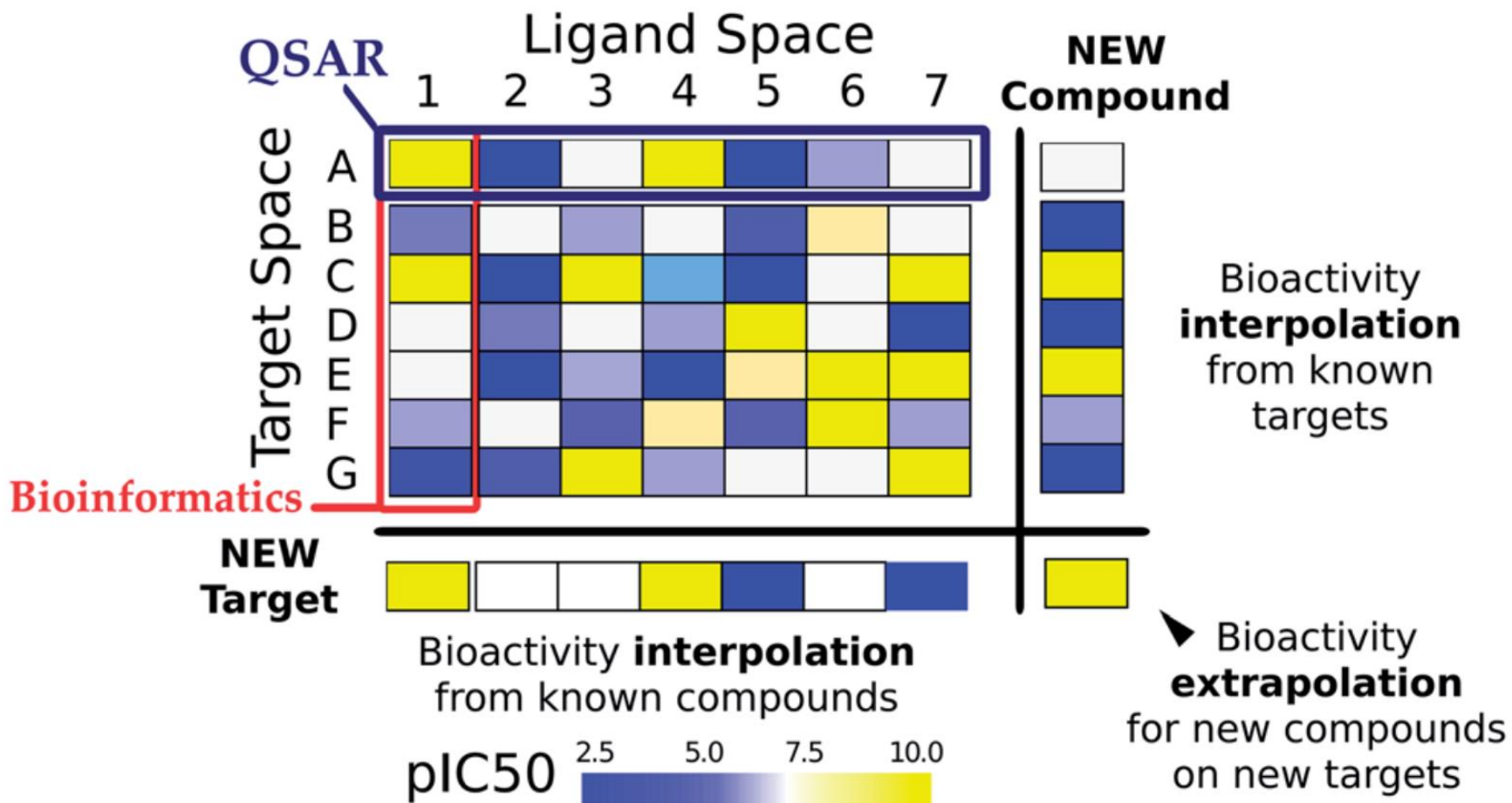


Cite this: *Med. Chem. Commun.*, 2015,
6, 24

Polypharmacology modelling using proteochemometrics (PCM): recent methodological developments, applications to target families, and future prospects



Proteochemometric





Proteochemometric

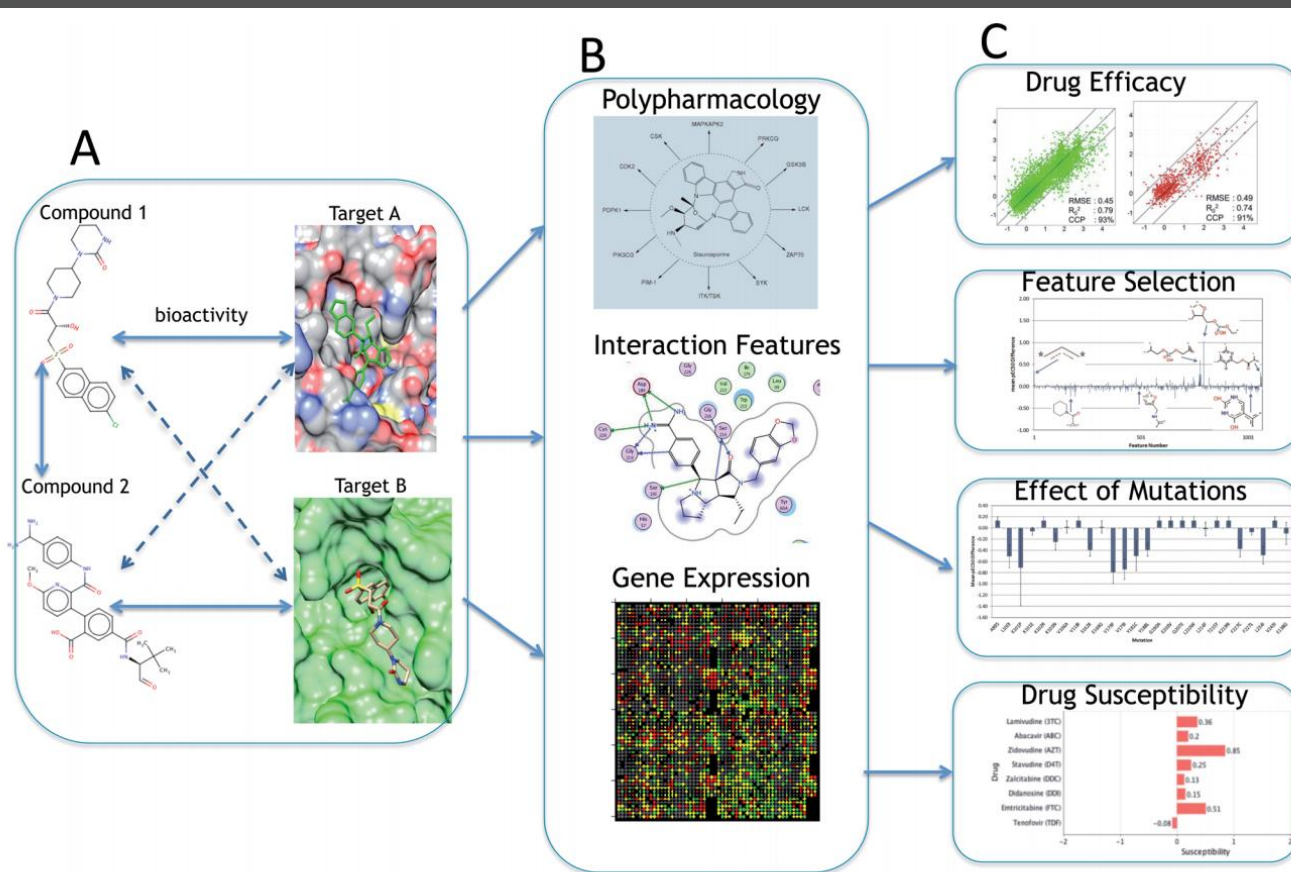


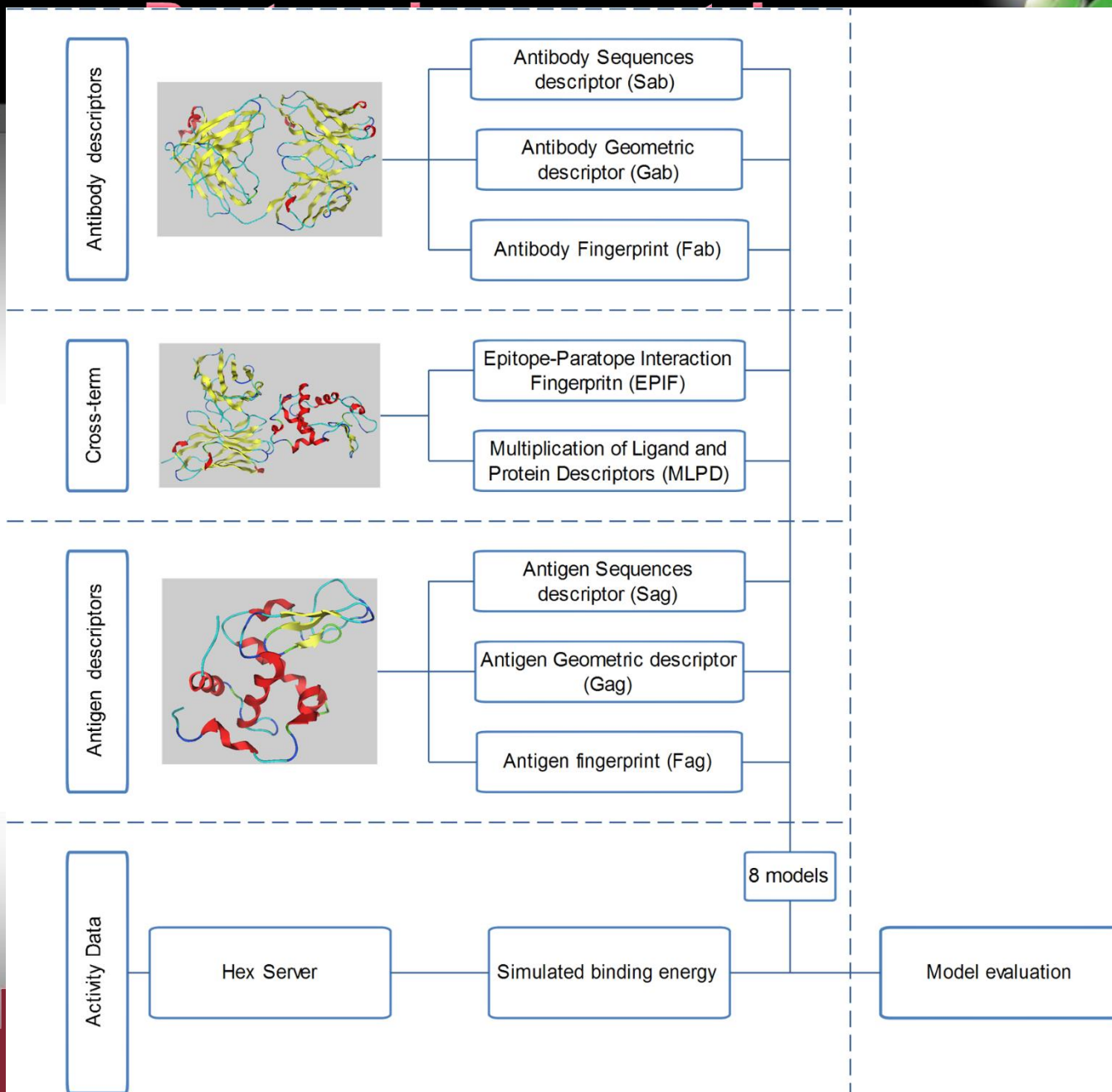
Fig. 2 A systematic overview of proteochemometric modelling. (A) shows the similarity between ligands and drug targets and the utilization of both types of information in PCM. (B) is the representation of different types of input features of ligand and target space (shared bioactivity profiles of ligands, binding pocket residues, gene expression in cell lines, mutational stability, etc.) which could be employed in a PCM model depending on the type of output variable. The third block (C) shows the various possible applications of PCM models including measurement of drug efficacy and susceptibility, effect of mutations on activity and compound–target feature selection.



Proteochemometric Modeling of the Antigen-Antibody Interaction: New Fingerprints for Antigen, Antibody and Epitope-Paratope Interaction

Tianyi Qiu, Han Xiao, Qingchen Zhang, Jingxuan Qiu, Yiyan Yang, Dingfeng Wu, Zhiwei Cao , Ruixin Zhu 

Published: April 22, 2015 • <https://doi.org/10.1371/journal.pone.0122416>





What to do if 3-D Structure of the Target is not known?

Homology Models

